Health and Income: Replication, Theoretical Model, Simulation, and Empirical Analyses

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Dedication

This research is dedicated to the people whose training, mentorship and life experience have guided my career and spiritual development. Most especially Engineer Rauf O. Atanda, Professor Robert Reed, Stuart Walker, and Howard Mahere (Lolly Man).

To my amazing life partner, Rangarirai Shalom Mahere for her priceless support and inspiration. She is the greatest and most valuable asset I acquired during the programme.

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Abstract

Health plays an important role in the economic growth process and increasing productivity concurrently creates better health outcomes. The stock of an individual's health increases as income rises as well as investment in health augmenting consumption. The increasing attention paid to the health-income nexus motivates this thesis to use macroeconomic theory, tools and methods to examine the link. This study first replicates a highly cited empirical work by Hartwig (2008) on Baumol's Cost Disease (BCD) to explain the rising trends of healthcare expenditure. The gaps identified during the replication prompt the designing of testable theoretical models of BCD in Chapter 3. The formulated BCD hypotheses are tested using two sets of panel data estimators that assume slope homogeneity and heterogeneity. In Chapter 4, a Monte Carlo simulation experiment is conducted to investigate the performance of recently developed "mean group type" panel estimators that are robust to cross-sectional dependence, slope heterogeneity, non-stationarity and endogeneity. The simulation experiment results inform the choice of the panel estimators used to examine the income elasticity of healthcare expenditure for selected African countries in Chapter 5. Overall, I find that Hartwig's (2008) study suffers from methodological flaws and the tested hypotheses revealno significant relationship to support the BCD predictions using an OECD dataset. From the simulation experiments, I find the Common Correlated Effect Mean Group (CCEMG) estimator to be the "best" on the dimensions of bias, efficiency, and coverage rates. Lastly, the empirical analysis using the dataset for 47 African countries and estimating with CCEMG provides no significant outcomes to support whether total, public and private health expenditures are either income inelastic or elastic i.e., health care is a necessity or luxury good.

Key words: Health expenditure, income, panel data, cross-sectional dependence, slope heterogeneity, factor models, endogeneity, OECD, Africa

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The paper titled "Is Health Care Infected by Baumol's Disease? Test of a New Model" has been submitted to the journal "Health Economics". The paper is extracted from Chapter 2 of the thesis.

Please detail the nature and extent (%) of contribution by the candidate:

Bob Reed did most of the work on the theoretical model in the chapter, and Andrea Menclova did much of the writing on the working paper, some of which was incorporated into the chapter. Akinwande did 100% of the data analysis and wrote a comprehensive first draft of the chapter." It is difficult to determine overall contribution, but if I had to give a number I would say that Akinwande's contribution was approximately 70% overall.

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Name: *Bob Reed* Signature: W Robert Reed Date: *19/06/2017*

Abbreviations

2WFE	Two-Way Fixed Effects
AIDS	Acquired Immune Deficiency Syndrome
AMG	Augmented Mean Group
BCD	Baumol’s Cost Disease
BIC	Bayesian Information Criteria
CA	Central Africa
CCEMG	Common Correlated Effects Mean Group
CCEP	Common Correlated Effect Pooled Estimator
CD	Cross-sectional Dependence
CI	Cross-section Independence
CIPS	Cross-sectional Augmented IPS
CRE	Cross-section Random Effects
DCCEMG	Dynamic Common Correlated Effects Mean Group
DGP	Data Generating Process
EA	East Africa
EMP	Total Employment
EUROSTAT	European Commission Statistics
FCA	Fragile and Conflict affected African states
FD	First Difference
FD-OLS	First Difference Ordinary Least Square
FE	Fixed Effects
FGLS	Feasible Generalised Least Square
FRA	Fragile Region
FSI	Fragile State Index
GDP	Gross Domestic Product
GHE	Government Health Expenditure

GHO	Global Health Observatory
GLS	Generalised Least Square
H	Health Sector
HCE	Healthcare Expenditure
HI	High Income
HIV	Human Immunodeficiency Virus
HW	Hartwig (2008a)
IDP	Internally Displaced People
IMF	International Monetary Fund
LIN	Lower Income
LM	Lagrange Multiplier
LMI	Lower Middle Income
LSHL	Health Share of Labour Force to Total
MDG	Millennium Development Goals
MG	Mean Group
N	Number of Cross-section Unit
NA	North Africa
NFR	Non-Fragile Region
NH	Non-Health Sector
NPS	Non-Progressive Sector
ODA	Official Development Assistance
OECD	Organisation for Economic Co-operation and Development
OPE	Out-of-Pocket Expenditure
PCSE	Panel-Corrected Standard Error
PHN	Ratio of Health to Non-Health Price Index
POLS	Pooled Ordinary Least Squares
PPP	Purchasing Power Parity

PROD	Productivity Per Employee
PS	Progressive Sector
PURT	Panel Unit Root Test
R&D	Research and Development
RCM	Random Coefficients Model
RE	Random Effects
RESET	Ramsey Regression Equation Specification Error Test
RGDP	Real Gross Domestic Product
RMSE	Root Mean Squared Error
SA	Southern Africa
SDG	Sustainable Development Goals
SEAR	South-East Asian Regional
SSA	Sub-Saharan Africa
T	Time
THE	Total Health Expenditure
TRE	Time period Random Effects
U.K	United Kingdom
U.S	United States
UMI	Upper Middle Income
WA	West Africa
WAGE	Total Wages
WDI	World Development Indicators
WHO	World Health Organisation
WSPE	Nominal Wage Per Employee

Chapter 1: Introduction

Chapter One

Introduction

1.1 Preamble

Improvements in human welfare and productivity are dependent on the individual's health status. Ill health and sickness have detrimental consequences for the capacity of humans to engage in economic activities (Bloom & Canning, 2003; Bloom, Canning, & Sevilla, 2004). Health is one of the main determinants of economic growth (Barro, 1996; Well, 2007). As a component of human capital development, it defines and enhances the productive capacity of the workforce in an economy. Similarly, economic growth provides an opportunity for technological advancement to further improve the health status of individuals. Thus, health plays an essential role in the economic growth process via human capital development, while increasing productivity simultaneously feeds back into better health outcomes.

Over the last four decades, following on seminal contributions by Grossman (1972a) and Newhouse and Phelps (1974), there has been increasing attention paid to the health-income nexus. Micro-level interest has focussed on the impact of health on human well-being, while macro-level analyses have focused on the growth consequences of health status. Health production has also received considerable attention and cost-effectiveness studies of various medical or lifestyle interventions abound. Of particular interest to policy makers and health economists is the cost of providing medical care services. These can either be financed by the public sector (i.e. government health care expenditure) or the private sector (i.e. out-of-pocket spending, private health insurance).

This thesis analyses the macro-level inter-relationships between healthcare expenditure and economic growth. In the relevant literature, research has evolved along different strands. One category of research focuses on the causes and consequences of rising medical spending. A second category analyses the effect of health status on economic growth. A third category is concerned with the growth effect of health care expenditure. Another research line investigates health-labour productivity (in terms of labour participation and numbers of hours worked). Yet another strand examines the consequences of demographic changes such as population aging and/or ethnic composition. Finally, more recently, empirical research has started to focus on the time-series properties (stationarity, cross-sectional dependence and cointegration) of health care expenditures (e.g. Baltagi & Moscone, 2010; De Mello-Sampayo & De Sousa-Vale, 2014; Moscone & Tosetti, 2010; Murthy & Okunade, 2016). The first and last categories combined are the main focus of this thesis. In particular, I study the causes of rising medical expenditures while carefully addressing their time-series properties.

1.2 Statement of the Problem and Rationale for this Study

Health contributes to the growth of a country through human capital development (Barro, 1996; Bloom et al., 2010; Bloom et al., 2004; Knowles & Owen, 1995, 1997; Narayan, Narayan, & Mishra, 2010; D. N. Weil, 2014; Well, 2007)[1]. This indicates that health is an input into a productive workforce. According to Grossman (1972b) , health is a durable capital stock that can be improved via investment in medical care and income. The effectiveness of medical care is determined not only by activities of skilled health professionals like physicians, but also through financing mechanisms and governance structures (see Newhouse, 1970; Pauly, 1987).

A key concern at the heart of public health policy is whether health production is efficiently organized and operated. Economic costs include wastage, misallocation and the draining of resources from more productive activities. Health care expenditures as a share of national output have more than doubled over recent decades in the OECD (Organisation for Economic Co-operation and Development). As a result, the cost side of the industry has become a focus of policy debate across the OECD countries (Baltagi & Moscone, 2010;

[1] There is a contradictory view that health proxied by life expectancy has a smaller effect on economic growth but a larger impact on population growth (Acemoglu & Johnson, 2007).

Baltagi, Moscone, & Tosetti, 2012; Hartwig, 2008b). In 1960, the OECD average of GDP spent on health care was 3.83%. By 2010, it had increased to 9.13%, a 138% rate of growth. While this upward trend was suspended during the global financial crisis of 2007/2008, health care spending has once again started to rise, especially in Europe (OECD, 2015) .

In an attempt to look for explanations of the rising health care spending, there has been a revival of interest in Baumol's Cost Disease (Baltagi et al., 2012; Baumol, 1967, 1993; Hartwig, 2008b, 2011a; Nixon & Ulmann, 2006; Oliveira Martins & De la Maisonneuve, 2006). However, the existing literature has been hampered by a fairly loose application of theory to empirical specification. This suggests the need for a theoretically-appropriate test of Baumol's Cost Disease hypothesis. Chapter 2 of this thesis replicates a highly cited empirical work in the area of BCD in order to better understand the concept, framework and existing gaps. Chapter 3 then attempts to fill these gaps by designing a testable theoretical model of Baumol's Cost Disease.

Another common hypothesis in the literature is that rising income is a major determinant of increasing health expenditures (see Gerdtham & Jönsson, 2000b; V. N. Murthy & A. A. Okunade, 2009; Prieto & Lago-Peñas, 2012). However, previous studies provide a wide range of estimates of the income elasticity of health care spending, and the appropriate model specification and estimation procedures are disputed. In Chapter 4, following Bond and Eberhardt (2013a), I conduct a replication of a Monte Carlo simulation experiment to investigate the performance of the recently developed "mean group type" panel estimators compared with the "pooled type" estimators. The outcomes of the simulation experiment inform the choice of the estimators used in Chapter 5 (discussed below).

In Chapter 5, I investigate the relationship between health care expenditures and income for African countries. In particular, I adopt a robust analytical framework from the previous simulation in order to appropriately control for technological spill-overs, endogeneity, cross-sectional dependence, interdependence of health policies across countries, and heterogeneity of unobserved effects. In addition to income, I include non-income determinants of health care spending which have so far received only little attention in the literature. Among those variables that have been identified are budget deficits or government fiscal capacity (Jönsson, 1996; Jönsson & Musgrove, 1997; Ke, Saksena, & Holly, 2011), institutional factors (see D. N. Weil, 2014), and official development assistance (Gbesemete & Gerdtham, 1992; Okunade, 2005). Chapter 5 investigates these determinants, paying particular attention to issues of measurement and conceptual design that have been noted elsewhere (see Cutler, McClellan, Newhouse, & Remler, 1998).

Chapter 6 summarises and concludes the entire thesis as well as identifies areas of further research. Finally, Chapter 7 describes and presents the estimation codes used in this thesis.

1.3 Research Questions

Emanating from the empirical, theoretical and analytical issues discussed above, the following research questions form the focus of this thesis:

I. Is the most cited research in the area of "Baumol Cost Disease" replicable and robust? (Chapter 2)
II. Is the health sector infected by a "cost and price disease"? (Chapter 3)
III. What is the comparative performance of the "mean group type" and "pooled type" panel data estimators under different set-ups? (Chapter 4)
IV. What drives macro-level health care expenditure in Africa? (Chapter 5)

Chapter 2: Replication of "What drives health care expenditure? --- Baumol's model of 'unbalanced growth' revisited" (*Journal of Health Economics, 27, 603-623*) by Hartwig (2008)"

Chapter Two

2.1 Overview of Hartwig (2008)

This chapter of the thesis replicates and assesses the robustness of the study by Hartwig (2008b, henceforth HW) on the determinants of health care expenditure (HCE) in OECD[2] countries. HW was motivated by the fact that rapidly rising health expenditure relative to gross domestic product (GDP) of developed nations, inclusive of OECD countries, has raised concerns among policy makers and analysts. The concerns stemmed from the unclear determinants of rising HCE. In particular, HW picks up on three main methodological concerns: First, for over three decades, most empirical studies have focused on national income/GDP as a determinant of health care expenditure. Several attempts have been made to identify other factors such as proximity to death and ageing as composite drivers of health expenditure. However, these have been largely unsuccessful, controversial and/or inconclusive.

Second, the most commonly employed theory (cf. Grossman (1972a) is only concerned with an individual's demand for health, rather than aggregate demand. This calls for a theoretical foundation for analysing the determinants of national health care expenditure. This theoretical gap motivated HW to revisit Baumol (1967) model of "unbalanced growth" in explaining the rapid rise in health care expenditure. HW empirically verified Baumol's model to examine non-income determinants that drive HCE.

Lastly, the unknown order of integration of health expenditure variables constitutes the third rationale for the HW study. Hartwig posited that to achieve robust and non-spurious results using health expenditure time series variables, it is better to employ variables in their stationary form when specifying a regression model. Thus, HW leveraged on the contribution of Gerdtham and Jönsson (2000b) that advocate the need to study growth rates of health

[2]Organisation for Economic Co-operation and Development (OECD)

expenditure instead of levels. This approach helps resolve the controversial issue of the degree of integration of the HCE panel time series. On this basis, HW employed a set of panel unit root tests to precisely determine the stationary form of HCE series and also incorporated the growth rate of health expenditure series in the adopted modelling approach.

The findings of HW have often been cited, especially his conclusion that wage increases in excess of labour productivity growth are a significant determinant of HCE. Specifically, HW hypothesized and showed that the value of the coefficient on the 'Baumol variable'[3] is (i) statistically different from zero; and (ii) close to one. Indeed, HW's empirical evidence indicated strong support for Baumol's model of 'unbalanced growth' and further established that the coefficients were in fact equal to one using Wald parameter restriction tests on all specifications as reported in Table 1 and 2 in his study (see Hartwig, 2008b, p. 610). HW concluded that the parameter estimate of 'Baumol's variable' being equal to one emanates from a prediction of Baumol's theory and his model can therefore serve as a theoretical foundation for investigating the determinants of health care expenditure.

HW's empirical contribution has been seen as significant as it provides another non-income factor that drives HCE from a theoretical perspective with an elasticity coefficient near unity. The study likewise suggested that labour prices (i.e. wages) play a significant role in explaining the continuous rise in HCE. The work has been cited 184 times as reported on Google Scholar (as of 24th February, 2017).

The relevance of HW in the macroeconomic field of health expenditure analysis motivates its selection for replication. This chapter re-analyses the data underlying HW for consistency and performs robustness checks.

[3] Defined as the difference between the growth rates of nominal wages and productivity per employee.

2.2 Replication Methods

2.2.1 HW Model and Data Description

HW investigated the impact of wage increases in excess of labour productivity on current health expenditure using a linear growth regression similar to Barros (1998) of the form:

$$y_{it} = \alpha X_{it} + e_{it} \tag{2.1}$$

where y_{it} is the log difference (growth rate) of HCE per capita in country i in year t. X denotes a vector of exogenous determinants including the "Baumol variable" defined as the log difference between nominal wages per employee and productivity:

$$Baumol = d\log\left(\frac{WAGE}{EMP}\right) - d\log\left(\frac{GDPR}{EMP}\right) \tag{2.2}$$

$$Baumol = d\log(WSPE) - d\log(PROD) \tag{2.3}$$

where $WAGE$ is nominal wages; $GDPR$ is Real Gross Domestic Product; EMP is total employment; $PROD$ is productivity per employee; and $WSPE$ is the nominal wage per employee. The expression (2.3) represents an 'unsplit Baumol variable', while HW also considered a split (/disaggregated) Baumol variable from (2.2) as:

$$Baumol = d\log(WSPE) - [d\log(GDPR) - d\log(EMP)] \tag{2.4}$$

Therefore, HW estimated the following split and unsplit Baumol's equations:

$$\begin{aligned} d\log HCE_{it} = {} & \alpha_0 + \alpha_1 d\log(WSPE)_{it} + \alpha_2 d\log(GDPR)_{it} \\ & + \alpha_3 d\log(EMP)_{it} + e_{it} \end{aligned} \tag{2.5}$$

$$d\log HCE_{it} = \beta_0 + \beta_1\ Baumol_{it} + e_{it} \tag{2.6}$$

where e_{it} is an error term and taken as white noise.

2.2.2 HW Estimation Techniques and Sample Description

HW estimated equations (2.5) and (2.6) using Pooled Ordinary Least Squares (POLS), Cross-section Random Effects (CRE), and Time period Random Effects (TRE). The latter two procedures allow the unobserved, “fixed component” of the error term to be associated either with a specific country or a specific year, respectively. The panel models were estimated for a sample of 19 OECD countries comprised of Australia, Austria, Canada, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, the Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, the United Kingdom and the United States of America. The unbalanced panel time series cover the period 1960 to 2005 and were sourced from OECD *Health Data* 2005 CD-ROM.

2.3 Sample Description and Summary Statistics

HW graciously provided the original data employed in his study on request. Using the data, this thesis was able to replicate HW’s Table 1 and 2 for specified models (2.5) and (2.6). It is essential to describe the panel time series characteristics of the data employed in the estimation of the panel regression models (2.5) and (2.6). However, HW does not report the sample characteristics. A closer look at my Table 2.1 indicates that the pooled average annual growth rate values of current health expenditure per capita (DLHCEP), nominal wages per employee (DLWSPE), real gross domestic product (DLGDPR), total employment (DLEMP), productivity per employee (DLPROD), and the wage-productivity gap (BAUMOL) in the OECD between 1960 and 2005 stood at 9.88%, 8.28%, 2.56%, 2.07%, 3.04%, 1.07%, 1.89%, and 6.72% respectively. This reflects the high growth rate of current health expenditure per capita, low labour productivity growth and a large wage-productivity gap in OECD countries.

Table 2.1: Descriptive Statistics for Hartwig's (2008) Pooled Original Data

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
DLHCEP	589	9.9%	7.2%	-9.2%	63.0%
DLWSPE	623	8.6%	7.3%	-15.6%	44.3%
DLGDPR	646	3.0%	2.6%	-7.6%	11.7%
DLEMP	761	1.1%	2.1%	-7.3%	24.3%
DLPROD	624	1.9%	2.3%	-19.3%	11.5%
BAUMOL	623	6.7%	7.0%	-4.5%	47.4%

The average values for individual countries are reported in Table 2.2. The mean values reveal that countries with high growth in the wage-productivity gap (such as Finland, South Korea, Netherland, Norway, U.K, France, and Germany) recorded the highest average annual growth rate of current health expenditure per capita (see Figure 2.1)[4].

Table 2.2: Descriptive Statistics for Hartwig's (2008) Original Data: By Country

Sample	DLHCEP	DLWSPE	DLGDPR	DLEMP	DLPROD	BAUMOL
Australia	9.9%	7.3%	3.6%	1.9%	1.6%	5.7%
Austria	7.9%	5.6%	2.6%	0.6%	1.9%	3.8%
Canada	8.2%	5.6%	3.1%	2.2%	1.1%	4.5%
Denmark	4.2%	7.3%	2.4%	0.5%	1.9%	5.4%
Finland	18.4%	21.2%	3.7%	1.9%	1.7%	19.5%
France	10.9%	10.2%	5.0%	1.2%	3.5%	6.8%
Germany	10.5%	8.3%	2.8%	0.3%	2.5%	5.9%
Iceland	6.6%	3.0%	2.6%	1.9%	0.5%	2.5%
Ireland	6.3%	10.3%	2.3%	0.1%	2.0%	8.3%
Italy	10.7%	7.2%	3.4%	0.9%	2.4%	4.9%
Netherland	12.5%	15.0%	6.8%	2.7%	4.3%	10.7%

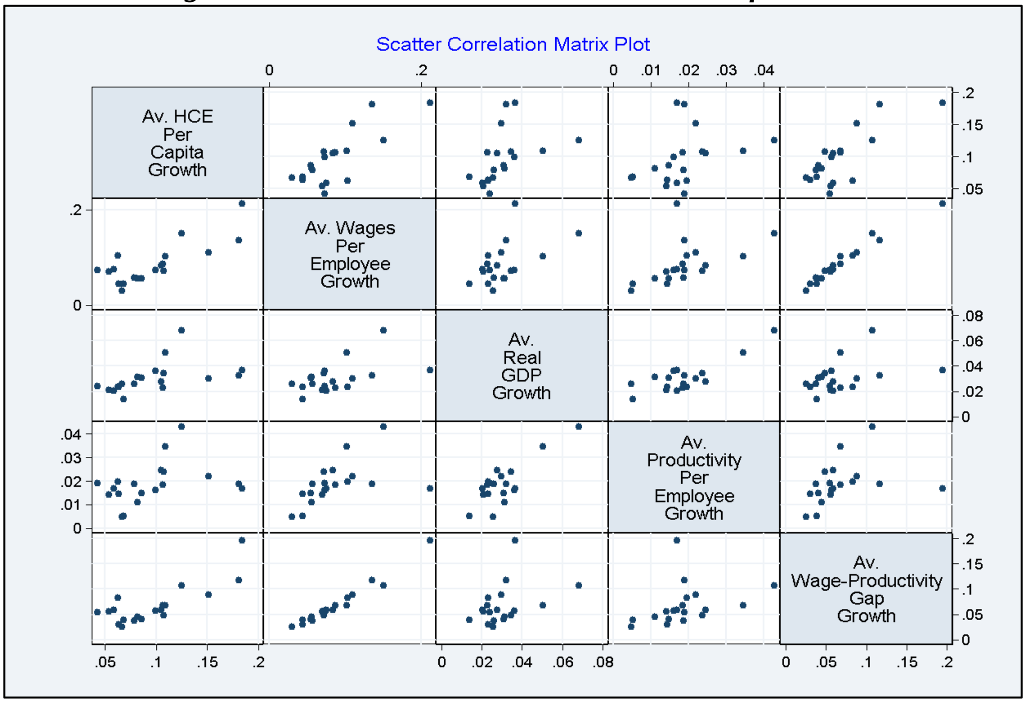
[4] This implies that there is a high correlation between current health expenditure per capita growth rates and labour prices (see Figure A2.1 in the Appendix) as well as with growth in the wage-productivity gap (see Figures A2.2 in the Appendix)

Sample	DLHCEP	DLWSPE	DLGDPR	DLEMP	DLPROD	BAUMOL
Norway	15.1%	11.0%	3.0%	0.8%	2.2%	8.8%
Portugal	5.9%	7.6%	2.0%	0.4%	1.7%	5.9%
South Korea	18.1%	13.6%	3.2%	0.9%	1.9%	11.7%
Spain	6.3%	4.5%	2.3%	0.7%	1.4%	3.0%
Sweden	6.8%	4.4%	1.4%	1.0%	0.5%	3.9%
Switzerland	5.4%	7.0%	2.1%	0.4%	1.4%	5.6%
UK	10.7%	8.6%	2.3%	0.3%	1.8%	6.8%
USA	8.6%	5.5%	3.1%	1.7%	1.5%	4.1%

The descriptive analysis of HW's data highlights two econometric issues. First, it identifies a concern that the individual country series are characterized by cross-sectional correlation or dependence. Figure 2.1 indicates a high degree of correlation between country-level explanatory variables. This is to be expected as these variables are linked by a country's history, climate, geography, labour mobility, economic relations, and health status. One would expect that countries that share these common factors would likewise have systematic error correlations.

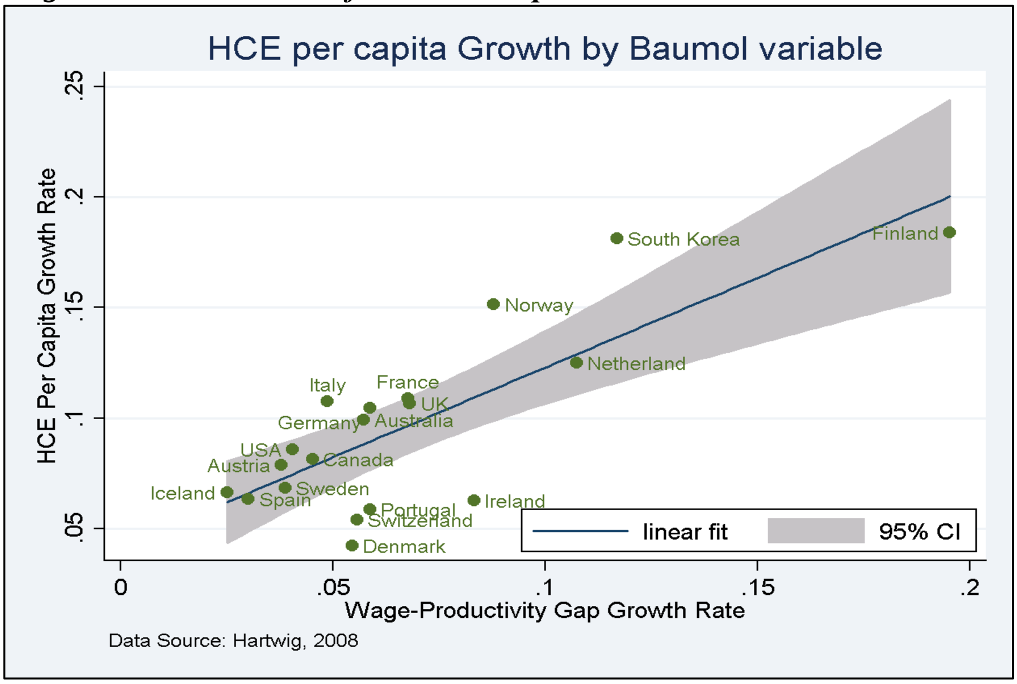
Second, as seen in Figure 2.2, while many countries align along a linear relationship between HCE per capita growth and wage-productivity gap growth, there are a disproportionate number of countries that lie outside the 95% confidence interval for this linear relationship. This suggests that there may be heterogeneity in the Baumol slope parameter across countries.

Figure 2.1: Scatter Correlation Matrix Plot of BCD Variables



These two econometric issues have potential implications for model specification and efficiency of standard panel data estimators, but were not addressed in HW's econometric analysis. In subsequent sections, the procedures adopted in addressing the aforementioned issues are discussed in detail.

Figure 2.2: Scatter Plot of HCE Per Capita Growth vs. Baumol's Variables



2.4 Pure Replication Results

The original dataset provided by HW was in EViews workfile format. The results reported in HW's Tables 1 and 2 (see Hartwig, 2008b, p. 610) are replicated in Tables 2.3 and 2.4. I was able to exactly reproduce HW's results using EViews 8.1, while obtaining somewhat different results using Stata (version 14.1). The reported t-ratios in HW's Tables 1 & 2 were based on EViews White cross-section standard errors and covariance method that Arellano (2003, p. 18) termed fixed T and large N robust standard errors. They correct bias for heteroskedasticity and 'within group' cross-section/ serial correlation. The Stata estimates use cluster robust standard errors. As noted by Reed & Ye (2011, p. 5), EViews and Stata use different degrees of freedom in calculating clustered standard errors.

The replication output using Stata revealed substantial differences from HW's main results in reported standard errors and t-statistics. The differences are highlighted in yellow. This is no doubt due to the different degree of freedom calculations employed by Stata and Eviews.

2.5 Robustness Checks

2.5.1 Robustness Check #1: Test of Cross-section Independence

Most of the recent theoretical and applied panel data econometric studies have emphasised the need to address the methodological issue related to cross-section or "between groups" dependence in error terms when dealing with panel data models.

Table 2.3: Results for Growth Rate Equations -- 'Baumol Variable' Split

Dep. Variable: Log difference of health care expenditure per capita [dlog(HCEP)]									
	OLS			Cross-Section R.E			Time Period R.E		
	HW Results (Eviews Output)	Replicated Results		HW Results (Eviews Output)	Replicated Results		HW Results (Eviews Output)	Replicated Results	
Variables		EViews Output	STATA Output		EViews Output	STATA Output		EViews Output	STATA Output
	5(I)	*5(II)*	*5(III)*	*5(IV)*	*5(V)*	*5(VI)*	*5(VII)*	*5(VIII)*	*5(IX)*
dlog(WSPE)	1.066***	1.066***	1.066***	1.064***	1.064***	1.064***	1.059***	1.059***	1.035***
	(28.557)	(28.557)	(48.50)	(27.561)	(27.561)	(48.22)	(27.155)	(27.155)	(28.73)
dlog(GDPR)	-0.339***	-0.339***	-0.339***	-0.351***	-0.351***	-0.351***	-0.308***	-0.308***	-0.233***
	(-3.951)	(-3.951)	(-4.85)	(-4.049)	(-4.049)	(-4.78)	(-3.571)	(-3.571)	(-2.80)
dlog(EMP)	0.601***	0.601***	0.601***	0.599***	0.599***	0.599***	0.588***	0.588***	0.574***
	(7.377)	(7.377)	(7.32)	(7.331)	(7.331)	(7.49)	(7.511)	(7.511)	(6.97)
Obs.	507	507	507	507	507	507	507	507	507

NOTE: Original results are taken from Table 1 in HW. The replicated results are identical. The explanatory variables are: dlog(WSPE) = log difference of wages and salaries per employee in the overall economy, dlog(GDPR)= log difference of real Gross Domestic Product (GDP), and dlog(EMP)= log difference of overall employment. The values shown in parentheses are t-ratios, based on White's Cross-section robust standard error and covariance. The Swamy-Arora GLS estimator was used to estimate the random effects models. The highlighted values indicated the areas of difference between the original and replicated results. *** denotes significance at 1% significance level

Table 2.4: Results for Growth Rate Equations -- 'Baumol Variable' Unsplit

Dep. Variable: Log difference of health care expenditure per capita [dlog(HCEP)]									
	OLS			Cross-Section R.E			Time Period R.E		
Variables	HW Results (Eviews Output)	Replicated Results		HW Results (Eviews Output)	Replicated Results		HW Results (Eviews Output)	Replicated Results	
		EViews Output	STATA Output		EViews Output	STATA Output		EViews Output	STATA Output
	6(I)	*6(II)*	*6(III)*	*6(IV)*	*6(V)*	*6(VI)*	*6(VII)*	*6(VIII)*	*6(IX)*
BAUMOL = dlog(WSPE)-dlog(PROD)	1.033***	1.033***	1.033***	1.016***	1.016***	1.016***	1.029***	1.029***	0.982***
	(34.763)	(34.763)	(37.31)	(32.763)	(32.763)	(31.58)	(34.204)	(34.204)	(19.12)
Obs.	507	507	507	507	507	507	507	507	507

NOTE: BAUMOL is the wage-productivity gap growth derived from the difference between dlog(WSPE) and dlog(PROD). dlog(WSPE) = log difference of wages and salaries per employee in the overall economy, and dlog(PROD) = log difference of labour productivity (real GDP per employee) in the overall economy. The values shown in parentheses are t-ratios, based on White's Cross-section robust standard error and covariance. The Swamy-Arora GLS estimator was used to estimate the random effects models. The highlighted values indicated the areas of difference between the original and replicated results. *** denotes significance at 1% significance level.

Cross-sectional correlation often emanates from unobserved common “shocks” and unobserved, time-invariant heterogeneous error components (Anselin, 2001; Baltagi, 2005; De Hoyos & Sarafidis, 2006; Eberhardt & Teal, 2011, 2014; Pesaran, 2004, 2006; Pesaran & Tosetti, 2011; Phillips & Sul, 2003; Robertson & Symons, 2000; Sarafidis & Wansbeek, 2012). This error component is a sub-component of the error term, incorporating spatial dependence and idiosyncratic pairwise dependence in the disturbance (De Hoyos & Sarafidis, 2006). Although the notion of cross-sectional dependence has been in existence since the 1930s, as noted in the works of Stephan (1934), Neprash (1934), and Fisher (1935), it is often ignored by researchers in panel model estimation.

The existence of cross-sectional correlation between error terms can have severe implications for the estimation of both coefficients and standard errors using standard panel data estimators (e.g., pooled ordinary Least Squares (POLS), fixed effects (FE) and random effects (RE) estimators). This can lead to poor policy decisions based on biased parameter estimates. The impact of cross-sectional dependence on estimation varies according to circumstances (Coakley, Fuertes, & Smith, 2006) but depends on two major factors: (i) the size of the average pairwise cross-sectional correlation; and (ii) the nature or source of the cross-sectional correlation (De Hoyos & Sarafidis, 2006).

For instance, in a case where the cross correlation of errors emanates from omission of common effects or unobserved spatial effects but is uncorrelated with the incorporated explanatory variables (i.e. $corr(u_i, X) = 0$), conventional panel estimators such as POLS, FE, and RE can produce misleading policy inference, inefficient estimators, and biased standard errors (Chudik & Pesaran, 2013; De Hoyos & Sarafidis, 2006; Phillips & Sul, 2003; Reed & Ye, 2011; Sarafidis & Robertson, 2009; Sarafidis & Wansbeek, 2012; Sarafidis, Yamagata, & Robertson, 2009). Accordingly, I test for cross-sectional independence in the data used by HW to estimate models (2.5) and (2.6) as reported in Tables 2.3 and 2.4 above.

For this purpose, the three most often used cross-sectional dependence test procedures - Pesaran (2004), Friedman (1937), and Frees (2004) cross-sectional dependence (CD) tests[5] - were employed to examine the between-group correlation in error terms (as a post-estimation diagnostic test) and panel time series variables (as a pre-estimation diagnostic test). De Hoyos and Sarafidis (2006, p. 490) indicated that the CD test is only valid as a post-estimation test after estimating a FE or RE model using the ***`xtcsd [ , pesaran friedman frees abs show]`*** Stata command. Baltagi and Moscone (2010, p. 807) emphasized the need to determine the size of cross-sectional dependence in underlying panel data using the Pesaran (2004) procedure (based on the Stata command ***`xtcd varnames`***) by regressing the series on their individual specific intercepts.

The test hypothesis of interest for this replication study emanates from model (2.1). Under the null hypothesis, e_{it} is assumed to be white noise (i.e. independent and identically distributed (iid)), and the alternative hypothesis is that e_{it} is cross-sectionally correlated, with no serial correlation. It should be noted that Frees and Friedman's tests were originally designed for static models, unlike Pesaran's CD test for static and dynamic models. Also, all the cross-sectional dependence tests are more suitable for cases where T is small and $N \to \infty$ (De Hoyos & Sarafidis, 2006) as well as where both are large (Chudik & Pesaran, 2013). Also, Pesaran's cross-sectional dependence test is more applicable for pre- and post-estimation testing, unlike other tests that are more appropriate as post-estimation tests (De Hoyos & Sarafidis, 2006).

Test Results

Table 2.5 presents the test results for cross-sectional correlation. It shows the average, country-specific correlation coefficients for the panel series full matrix and off-diagonal matrix

[5] Full description of all the cross-sectional dependence tests are presented at the appendix

elements, as well as Pesaran's cross-sectional dependence test statistics. The results indicate high positive, pairwise cross-sectional correlation of panel time series for current health expenditure per capita growth, wages and salaries per employee growth (as a proxy for labour prices), real GDP growth, and wage-labour productivity gap growth. The results further reveal the presence of cross-sectional dependence based on Pesaran's CD test statistics for each variable. The null hypothesis of cross-sectional independence is rejected at the 1% significance level.

Table 2.5: Panel Time Series Cross-Sectional Dependence Test Results

Variables	$\bar{\hat{\rho}}$	$\left|\bar{\hat{\rho}}\right|$	CD_{PES}
dlog(HCEP)	0.442	0.445	26.53***
dlog(WSPE)	0.509	0.554	32.45***
dlog(GDPR)	0.332	0.36	19.77***
dlog(EMP)	0.227	0.298	13.06***
dlog(PROD)	0.146	0.241	8.63***
Baumol	0.528	0.556	32.99***

Note: $\bar{\hat{\rho}}$, $\left|\bar{\hat{\rho}}\right|$, and CD_{PES} are respective average of the full elements of the cross-sectional correlation matrix of the series; average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series; and Pesaran (2004) CD test statistic.

*** denotes significance at 1% significance level

As a result of the statistics and tests above, I conclude that the individual country, panel data series employed in HW's study are correlated, likely due to similar patterns of health care reforms and common macroeconomic shocks.

In Table 2.6, I investigate the presence of "between groups" correlation in country-specific residuals using parametric and non-parametric correlation techniques as well as Pesaran's cross-sectional dependence test. The standard (or parametric) average absolute correlation indicates positive pairwise correlation coefficients of all the estimated residuals from replicated models 2.5 (VI & IX) and 2.6 (VI & IX). Also, the pairwise average Spearman rank correlation estimates from the models are found to be positive and high above 0.5. This indicates that the upper-diagonal has high positive and negative elements of country-specific pairwise correlations coefficients, which cancel each other out during averaging. This problem invalidates Friedman's cross-sectional dependence (CD) test. As a result, I do not place much weight on the finding that Friedman's CD test does not reject the null of cross-sectional independence. In contrast, Frees' CD test, based on the average sum of squares of the rank of pairwise correlations, rejects the null hypothesis of cross-sectional independence at the 1% significance level. Similar results are obtained using Pesaran's CD test. As a result, I conclude that the models' error terms are characterised by significant cross-sectional dependence.

Table 2.6: Estimated Residual Cross-sectional dependence Tests Results

	Model	$\lvert\bar{\hat{\rho}}\rvert_{PW}$	$\lvert\bar{\hat{\rho}}\rvert_{RK}$	CD_{PES}	CD_{FRI}	CD_{FRE}
2.5(VI)	**Cross-section RE**	0.180	0.510	2.911***	8.716	5.106***
2.5(IX)	**Time Period RE**	0.196	0.503	-3.080***	8.211	4.892***
2.6(VI)	**Cross-section RE**	0.175	0.545	1.874*	16.547	5.208***
2.6(IX)	**Time Period RE**	0.192	0.507	-3.052***	3.663	4.732***

Note: $\lvert\bar{\hat{\rho}}\rvert_{PW}$ and $\lvert\bar{\hat{\rho}}\rvert_{RK}$ are average absolute value of the off-diagonal elements of the cross-sectional pairwise and Spearman rank correlation matrix of residuals respectively.

CD_{PES} , CD_{FRI} , and CD_{FRE} are Pesaran (2004), Friedman (1937), and Frees (1995, 2004) cross-sectional dependence test statistics with the null hypothesis of cross-sectional independence.

*; **; and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

The findings above potentially causes a problem for HW's analysis, because the standard panel estimators (POLS and RE) used in HW do not correct for the cross-sectional dependence of residuals. As a result, the POLS and RE estimators are, at best, at risk of being inefficient with biased standard errors. The next section investigates alternative estimators that address these, and other, issues.

2.5.2 Robustness Check #2: Non-stationarity, Cross-Sectional Dependence and Heterogeneous Slope Estimators

The preceding exploratory data analysis has determined that the relationship between HCE per capita growth and wage-labour productivity growth in OECD countries is likely heterogeneous, which I speculate is due to differential health policies, labour forces, and prices across countries. To account for heterogeneous effects, and to control for cross-sectional dependence and non-stationarity of unobservable factors, I next consider some recent panel data estimators that are designed to address these econometric issues (for detailed assumptions and properties see Banerjee, Eberhardt, and Reade (2010); (Beck & Katz, 2007; Bond & Eberhardt, 2009; Chudik & Pesaran, 2013; Eberhardt & Teal, 2010, 2011, 2014; Pesaran, 2006; Pesaran & Smith, 1995; Poi, 2003; Reed & Ye, 2011; Swamy, 1970). These estimators include Swamy (1970) Generalised Least Squares (GLS) estimator for the Random Coefficients Model (RCM); Pesaran and Smith (1995) Mean Group (MG) estimator; Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) estimator; and the Augmented Mean Group (AMG) estimator by Bond and Eberhardt (2009) and Eberhardt and Teal (2010)[6].

These panel data estimators can accommodate at least one of the three main identified econometric issues to precisely estimate the determinants of HCE per capita growth across OECD countries. The replicated results for split and un-split Baumol's models using the estimators robust to heteroskedasticity, and serial correlation are shown in Tables 2.7 and 2.8, respectively. All the coefficients were found to have the same signs and significances as reported by HW, though coefficient sizes were different[7]. The non-stochastic heterogeneous slope models (MG, CCEMG and AMG) are augmented with a common country trend to enhance their performance and accuracy as suggested in a Monte Carlo simulation by Bond

[6] Brief description of the considered estimators is presented in Table A2.1 in the appendix.
[7] The scatter plots of the estimated country specific coefficients for each considered estimator are shown in the appendix (Figure A2.3, A2.4, A2.5, and A2.6)

and Eberhardt (2013b). As shown in Tables 2.7 and 2.8 below, under the RCM, the null hypothesis of a homogeneous slopes is rejected, which implies that the slopes are heterogeneous across cross-section units. The replicated average cross-section coefficients for the Baumol variable (0.964) in Table 2.8 under the RCM and MG without trend is less than HW's Baumol coefficient of 1.016 using a robust cross-sectional RE estimator. When the MG specification is augmented with heterogeneous country trends, a lower Baumol's coefficient of 0.886 is recorded, resulting in a smaller root mean squared error (RMSE).

Table 2.7: Estimator Sensitivity Analysis of 'Baumol Variable' Split Model [2.5]

Dep. Variable: Log difference of health care expenditure per capita [dlog(HCEP)]							
Replicated Results							
	RCM	**MG**		**CCEMG**		**AMG**	
Variables	**No Trend**	**No Trend**	**With Trend**	**No Trend**	**With Trend**	**No Trend**	**With Trend**
	2.5(X)	*2.5(XI)*	*2.5(XII)*	*2.5(XIII)*	*2.5(XIV)*	*2.5(XV)*	*2.5(XVI)*
dlog(WSPE)	1.012***	1.058***	1.049***	0.839***	0.842***	0.905***	0.884***
	(17.25)	(38.55)	(15.79)	(8.07)	(7.98)	(23.15)	(14.95)
dlog(GDPR)	-0.398***	-0.420***	-0.437***	-0.270***	-0.272***	-0.349***	-0.381***
	(-3.39)	(-4.34)	(-5.69)	(-2.67)	(-2.67)	(-4.26)	(-5.29)
dlog(EMP)	0.573***	0.556***	0.527***	0.591***	0.595***	0.517***	0.494***
	(4.29)	(4.85)	(4.35)	(4.89)	(4.61)	(5.52)	(5.41)
Country Trend			0.00004		0.0002		0.00007
			(0.12)		(0.81)		(0.27)
$H_0 : \beta_1 = ... = \beta_P$	163.68***	-	-	-	-	-	-
$RMSE$	-	0.0286	0.0279	0.0243	0.0240	0.0264	0.0258
$\lvert\bar{\hat{\rho}}\rvert$	-	0.183	0.188	0.204	0.205	0.191	0.198
CD_{PES}	-	1.66*	1.37	-2.84***	-2.62***	-2.85***	-2.61***

NOTE: dlog(WSPE) = log difference of wages and salaries per employee in the overall economy, dlog(GDPR)= log difference of real Gross Domestic Product (GDP), and dlog(EMP)= log difference of overall employment. The values shown in parentheses are t-ratios, based on conventional robust standard error and covariance matrix estimates. The Swamy (1970) GLS estimator was used to estimate the random coefficients Model (RCM); the Pesaran and Smith (1995) Mean Group (MG) estimator was employed to estimate the MG labelled panel model; the Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) Estimator was used to estimate the CCEMG labelled panel model; the Augmented Mean Group (AMG) Estimator by Bond and Eberhardt (2009); Eberhardt and Teal (2010) was employed for estimate the AMG labelled panel model; The null hypothesis in the lower panel is a test of parameter consistency; RMSE = Root Mean Squared Error; $\lvert\bar{\hat{\rho}}\rvert$ and CD_{PES} are respective average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series; and Pesaran (2004) CD test statistic.

*; **; and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Table 2.8: Estimator Sensitivity Analysis of 'Baumol Variable' Unsplit Model [2.6]

Dep. Variable: Log difference of health care expenditure per capita [dlog(HCEP)]							
Replicated Results							
	RCM	**MG**		**CCEMG**		**AMG**	
Variables	**No Trend**	**No Trend**	**With Trend**	**No Trend**	**With Trend**	**No Trend**	**With Trend**
	2.6(X)	*2.6(XI)*	*2.6(XII)*	*2.6(XIII)*	*2.6(XIV)*	*2.6(XV)*	*2.6(XVI)*
Baumol=dlog(WSPE)-dlog(PROD)	0.964***	0.964***	0.886***	0.789***	0.759***	0.762***	0.761***
	(19.18)	(25.50)	(23.34)	(10.77)	(10.72)	(16.00)	(15.51)
Country Trend			-0.001		0.0003		0.0002
	-	-	(-2.16)	-	(0.74)	-	(0.58)
$H_0 : \beta_1 = ... = \beta_P$	118.44***	-	-	-	-	-	-
$RMSE$	-	0.0319	0.0308	0.0285	0.0277	0.0293	0.0282
$\lvert\bar{\hat{\rho}}\rvert$	-	0.178	0.188	0.200	0.197	0.192	0.190
CD_{PES}	-	2.52**	2.48**	-2.79***	-2.85***	-3.05***	-3.16***

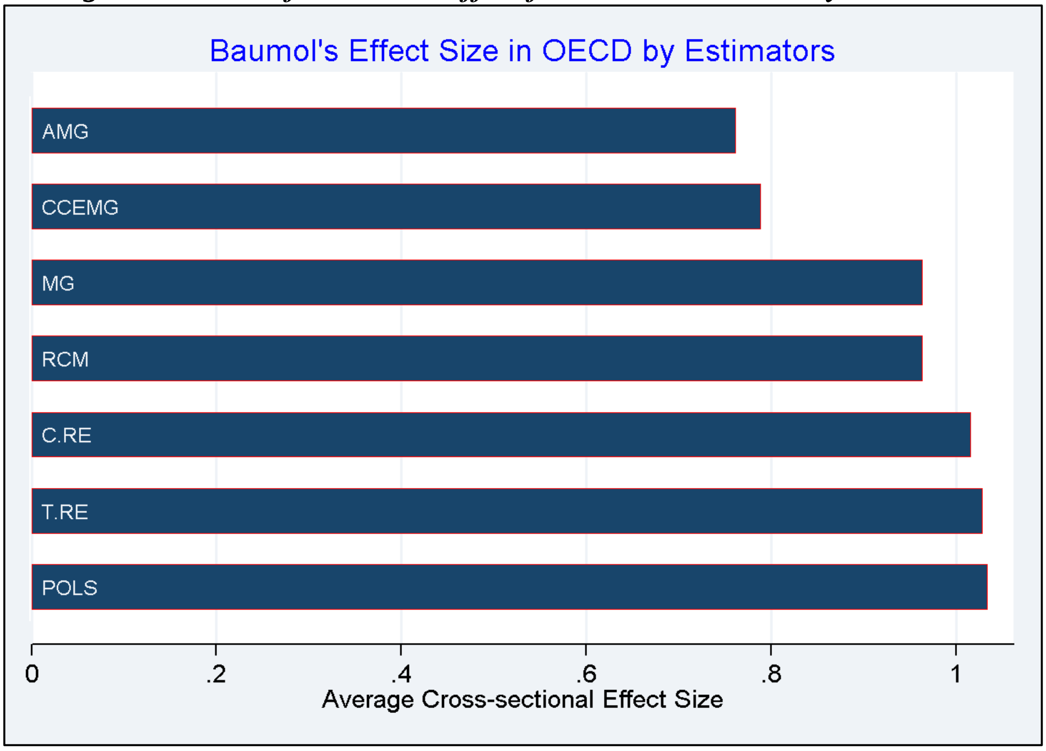
NOTE: BAUMOL is the wage-productivity gap growth derived from the difference between dlog(WSPE) and dlog(PROD). dlog(WSPE) = log difference of wages and salaries per employee in the overall economy, and dlog(PROD) = log difference of labour productivity (real GDP per employee) in the overall economy. The values shown in parentheses are t-ratios, based on conventional robust standard error and covariance matrix estimates. The Swamy (1970) GLS estimator was used to estimate the random coefficients Model (RCM); the Pesaran and Smith (1995) Mean Group (MG) estimator was employed to estimate the MG labelled panel model; the Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) Estimator was used to estimate the CCEMG labelled panel model; the Augmented Mean Group (AMG) Estimator by Bond and Eberhardt (2009); Eberhardt and Teal (2010) was employed for estimate the AMG labelled panel model; The null hypothesis in the lower panel is a test of parameter consistency; RMSE = Root Mean Squared Error; $\lvert\bar{\hat{\rho}}\rvert$ and CD_{PES} are respective average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series; and Pesaran (2004) CD test statistic.

*; **; and *** denote significance at 10%, 5%, and 1% significance levels, respectively.

Similarly, the estimators that have the potential to account for non-stationarity of observable and unobservable variables, slope heterogeneity and endogeneity created by the common factor shock (Eberhardt & Teal, 2010, p. 5), namely, CCEMG and AMG, produce estimates of Baumol's coefficient between 0.789 and 0.759 as reported in Table 2.8. These compare to HW's Baumol estimates between 1.016 and 1.033 (cf. Table 2.4). Figure 2.3 compares the estimated Baumol coefficients across the different estimators.

It is evident from Tables 2.7 and 2.8 that the performance of the estimators improves based on the RMSE values, especially for MG with trend, CCEMG and AMG. Also, the average absolute value of the off-diagonal cross-sectional correlation coefficients of these estimators is less than 0.21, compared to an average value of 0.51 reported in Table 2.6 for HW's estimators. Pesaran's cross-sectional dependence test results in Tables 2.7 and 2.8 indicate rejection of the null hypothesis of cross-section independence of residuals with the exception of the split Baumol's model under the MG with trend.

Figure 2.3: Size of Baumol's Effect for OECD Countries by Estimators



A comparison of the off-diagonal cross-sectional correlations of residuals and CD test statistics between HW's panel estimators (CRE and TRE) and the more robust MG, CCEMG and AMG estimators indicates that, while "between group" residual correlation continues to exist with the latter estimators, it is of generally smaller magnitude.

2.5.3 Robustness Check #3: Analysis of HW's Main Finding

My final check is also my most important. It consists of a closer investigation of HW's finding of a unit coefficient for the Baumol variable. This is HW's main empirical contribution. This result is based on two parts. First, HW tests whether the split Baumol model can be reduced to the unsplit model. After determining that it can be, HW then tests whether the coefficient on the resulting Baumol variable is equal to 1.

Recall that the Baumol variable is defined by equation (2.4):

$$Baumol_{it} = dlog(WSPE)_{it} - dlog(GDPR)_{it} + dlog(EMP)_{it}.$$

A sufficient condition for the three explanatory variables to be combined into a single, Baumol variable is that the coefficients on the three component variables sum to 1 in equation (2.5) (see below).

$$dlog(HCE)_{it} = \alpha_0 + \alpha_1 dlog(WSPE)_{it} + \alpha_2 dlog(GDPR)_{it} + \alpha_3 dlog(EMP)_{it} + e_{it}.$$

Specifically, this implies that $\alpha_1 + \alpha_2 + \alpha_3 = 1$. Inexplicably, HW does not test this restriction. Rather, he tests the (incorrect) restriction $\alpha_1 + \alpha_2 - \alpha_3 = 0$.[8] He fails to reject this hypothesis, and (falsely) concludes that this allows him to combine the variables into a single Baumol variable. It is correct to point out that HW's restriction is not appropriate. Unfortunately, the restriction $\alpha_1 + \alpha_2 + \alpha_3 = 1$ is also not correct. In order to be able to combine the three separate variables on the RHS (right hand side) of equation (2.5) to get a single regressor variable defined in Eequation (2.4) the appropriate restrictions are: $\alpha_1 = -\alpha_2$ and $\alpha_1 = \alpha_3$ (the third restriction $\alpha_3 = -\alpha_2$ is implied by the first two, so there are two

[8] See next to last paragraph on page 610 of Hartwig (2008b).

independent restrictions). This gives a common coefficient β_1 on each component as the Baumol variable.

The top panel of Table 2.9 mostly confirms HW's results for the (incorrect) hypothesis test. Of the 10 different models/estimators used to estimate the split Baumol specification of equation (2.5), only the Time Period Random Effects (TRE) model produces a significant test result, albeit at the 10 percent significance level. It is interesting to note that this contrasts with HW's finding of an insignificant test result for the TRE model. The reason for the discrepancy is due to the previously noted fact that Stata and Eviews produce different estimates for the TRE model (cf. Tables 2.3 and 2.4 above).

When I turn to testing the correct restriction, I obtained clearresults. Interestingly, had HW tested the correct hypothesis, he would have concluded that it was not appropriate to combine these components into a single Baumol variable. The test results for the POLS, CRE, and TRE models all soundly reject the null hypothesis at the 1 percent level of significance. Also, the RCM and various mean group estimators all return significant test results excluding CCEMG in the two cases for second restriction tes, which can be interpreted as not strongly supporting the aggregation of the separate components into a single Baumol variable.

The bottom panel of Table 2.9 tests the unsplit Baumol model. Of particular interest is the test of $\beta_1 = 1$, which HW takes as consistent with Baumol's model of "unbalanced growth." Using the same three models/estimators as HW, I likewise fail to reject the null that $\beta_1 = 1$, and thus confirm HW's finding in support of Baumol's model. However, when I use alternative models/estimators, the majority of these models strongly reject this hypothesis. As the CCEMG and AMG models are particularly well-suited to handle cross-sectional dependence in the errors, and as I have uncovered strong evidence of the same in HW's data, I conclude that these results constitute evidence against HW's main empirical result.

2.6 Conclusion

This study replicates Hartwig (2008b) and performs a variety of robustness checks. Using the same statistical package that HW used (Eviews), I am able to successfully replicate his findings for the split and unsplit Baumol panel models. However, when I re-estimated the models using Stata Version 14.1, I found discrepancies with the estimates reported by HW.

Table 2.9: Wald Coefficient Restriction Test Results

Model		Incorrect Restriction STATA	Correct Restriction STATA	
		$H_0: \alpha_1 + \alpha_2 - \alpha_3 = 0$	$H_0: \alpha_1 = -\alpha_2$	$H_0: \alpha_1 = \alpha_3$
(2.5)	POLS [F-statistic]	1.11	111.53***	26.31***
	Cross-section R.E [Chi-square]	0.90	100.26***	26.66***
	Time Period R.E [Chi-square]	3.51*	95.64***	20.78***
	RCM [Chi-square]	0.03	19.21***	6.97***
	MG [Chi-square]	0.27	39.91***	17.96***
	MG + Trend [Chi-square]	0.29	36.27***	14.28***
	CCEMG [Chi-square]	0.01	15.41***	2.43
	CCEMG + Trend [Chi-square]	0.02	15.12***	2.18
	AMG [Chi-square]	0.09	37.43***	14.64***
	AMG + Trend [Chi-square]	0.00	29.00***	12.87***
		$H_0: \beta_1 = 0$	$H_0: \beta_1 = 1$	
(2.6)	POLS [F-statistic]	1391.75***	1.4	
	Cross-section R.E [Chi-square]	997.57***	0.26	
	Time Period R.E [Chi-square]	365.38***	0.12	
	RCM [Chi-square]	367.8***	0.51	
	MG [Chi-square]	650.50***	0.93	
	MG + Trend [Chi-square]	544.60***	9.04***	
	CCEMG [Chi-square]	115.96***	8.32***	
	CCEMG + Trend [Chi-square]	114.86***	11.60***	
	AMG [Chi-square]	255.88***	25.00***	
	AMG + Trend [Chi-square]	240.58***	23.85***	

NOTE: The restrictions come from testing the coefficients in the split Baumol model (cf. equation 2.5). The estimators are given by POLS = Pooled Ordinary Least Squares; R.E = Random Effect; RCM = Random Coefficients Model; MG = Mean Group; CCEMG = Common Correlated Mean Group; AMG = Augmented Mean Group.

*, **, and *** denotes rejection of the null hypothesis at 10%, 5% and 1% significance level respectively.

HW's findings support Baumol's theoretical prediction that the effect of wage-labour productivity gap growth on HCE per capita growth is equal to one. My replication of HW's models produces mixed results. The "best" models, in the sense that they are most appropriate for data characterised by cross-sectional dependence (i.e., the CCEMG and AMG models), produce substantially different results from HW and challenge his conclusion in favour of Baumol's "unbalanced growth" model.

To summarise, this chapter contributes to the body of knowledge by identifying and addressing some of the estimation and theoretical issues in HW's empirical analysis. In particular, five econometric issues were addressed: (1) cross-sectional correlation of observable and unobservable series, (2) non-stationarity of unobservable common factors, (3) homogeneity of slope coefficients across countries, (4) non-correlation between explanatory variables and the unobservable error term, and (5) correct specification of a test of the Baumol model.

Robustness checks presented in this chapter accounted for the aforementioned issues in three ways: I first examined the presence of cross-sectional correlation of observable and unobservable series in the model and found the presence of 'between group' correlation in the panel time series variables employed by HW. I then estimated residuals from the naïve estimators used by HW and found them to be cross-sectionally dependent with an average off-diagonal correlation coefficient of 0.5. Second, I used robust and less restrictive panel data estimators that account for slope heterogeneity, cross-sectional dependence, non-stationarity of unobservable factors, and endogeneity emanating from common, unobservable shocks. These estimators produced estimates of the effect of wage-labour productivity gap growth on HCE per capita growth that were smaller in magnitude than those found by HW.

Third, I undertook further investigation of HW's test of the Baumol hypothesis. I found that HW tested the wrong restriction pursuant to combining the component variables into a single Baumol variable. A test of the correct restriction produced clear results that the variables in the split model can not be combined to derive a single Baumol variable. Likewise, a re-analysis of HW's test of Baumol's unit coefficient resulted in mixed results, with the more robust panel data estimators producing estimates that disconfirmed HW's findings.

In conclusion, it should be noted that while there is some evidence that labour prices are a significant determinant of HCE per capita growth rate, estimates suggest a smaller effect than the value of 1.02 reported by Hartwig (2008b). For example, recent studies such as Bates and Santerre (2013) report much lower estimates (less than 0.04) using labour prices in the health sector rather than aggregated, economy-wide labour prices as used by HW. This further supports our finding that it might not be legitimate to sum all the variables in HW's split model into one variable to directly measure "Baumol's effect". On a related note, the theoretical basis relating HW's empirical tests to Baumol's model is tenuous and not well developed. There is no mathematical model that directly derives the unitary coefficient on the Baumol variable as a necessary consequence of Baumol's model. Also, no robust model framework in the literature that accounts for endogeneity of Baumol's variable. Bates and Santerre (2013) suggested that output shock can affect Baumol's variable in the health sector through its impact on wages and productivity. However, the lack of a strong theoretical basis to HW's empirical analysis serves as the motivation for the next chapter.

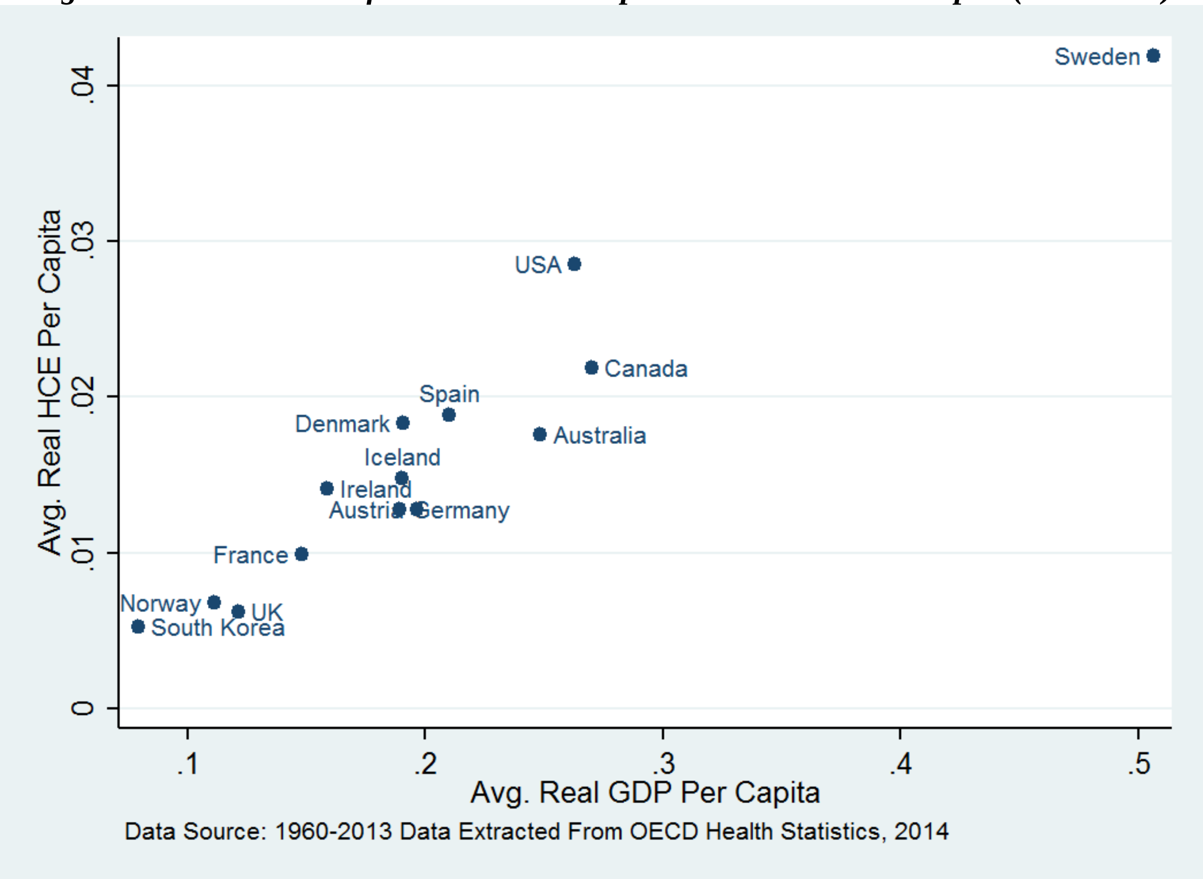
Chapter 3: Is health care infected by Baumol's Cost Disease? Test of a new theoretical model

Chapter Three

3.1 Introduction

Health is essential to the productivity of human capital and overall economic growth. The increasing cost[9] of health care services has received much attention from health managers, health economists and public policy makers. For instance, health care spending has been rising across developed countries. OECD countries with high average per capita income growth have recorded high growth of health care expenditure per capita between 1960 and 2014 as shown in Figure 3.1.

Figure 3.1: Scatter Plot of Real HCE Per Capita vs. Real GDP Per Capita (1960-2013)



The strong relationship between rising income and health spending is a common finding in the literature (Costa-Font, Gemmill, & Rubert, 2011; Gerdtham & Jönsson, 2000b; V. N.

[9] The focus of BCD is the price component of health expenditure (Q*Ph). Cost and expenditure are used interchangeably as synonyms in this analysis.

Murthy & A. A. Okunade, 2009; Prieto & Lago-Peñas, 2012). However, there are still controversies in the literature about the size of the income elasticity of health expenditure (Gerdtham & Jönsson, 2000b) and studies in this area are confronted with specification and estimation issues (Costa-Font et al., 2011). Also, there is a paucity of theoretical foundation for most documented studies on determinants of health spending. The field of health economics lacks sound macroeconomic theory (Gerdtham & Jönsson, 2000b) and analyses of significant non-income factors (Baltagi & Moscone, 2010; Baltagi et al., 2012; Hartwig, 2008b) to provide an explanation for the rising cost of health care.

In an attempt to explore other non-income determinants and provide a strong theoretical explanation of rising health care spending, there has been a revival of interest in Baumol's Cost Disease (Baltagi et al., 2012; Baumol, 1967, 1993; Hartwig, 2008b, 2011a; Nixon & Ulmann, 2006; Oliveira Martins & De la Maisonneuve, 2006). William Baumol in his 1993 paper, "*Health care, education and the cost disease: A looming crisis for public choice*" made the pioneering empirical attempt to use his 1967 theoretical study on "Cost Disease" hypothesis for health care spending analysis. Prior to that, the theory was first discussed in Baumol and Bowen (1965) in the context of the performing arts industry. Baumol and Bowen (1965, p. 499) theoretical explanation of cost development relative to productivity growth was based on a two-sector model in which one sector, by virtue of its production technology, enjoys regular productivity increases, while the other sector, by nature of its production technology, does not.

Baumol (1967) used the same theory to explain rising costs in the health care industry - considered as a non-progressive sector whose productivity is stable and cost increases are unavoidable. The central theoretical idea of the Baumol Cost Disease (BCD) model according to Baumol (1967, p. 51) is to explain the behaviour of labour-intensive industries such as health care whose demand continually increases, without corresponding increases in output per man-hour. Because of stagnant productivity growth and little substitutability of capital for labour, real costs inexorably climb over time.

However, a key challenge in investigating BCD is the development of a theoretically-appropriate empirical test. This thesis fills this gap by building a new theoretical model that is: (i) strictly based on Baumol's axioms; and (ii) directly testable empirically. Previous attempts (Bates & Santerre, 2013; Baumol, 1993; Colombier, 2012, 2017; Hartwig, 2005, 2008a, 2008b, 2010, 2011a, 2011b; Martins & de la Maisonneuve, 2006; Nixon & Ulmann, 2006; Nordhaus, 2008) to provide a testable hypothesis of BCD using different approaches have not explicitly and comprehensively linked the model specification to the full set of key axioms of the theory. This issue is further discussed in section 3.3 below.

3.2 Baumol's Cost Disease: Characteristics and Propositions

According to Baumol (1967), the non-technologically progressive sector (such as the health care industry) with constant output per man-hour (i.e. productivity) does not benefit from productivity-induced cost savings. This distinguishes the non-technologically progressive sector from the progressive sector, where technology promotes innovation, research and development and increasing economies of scale. In the technologically progressive sector (such as manufacturing) output per man-hour grows rapidly, offsetting, and more than offsetting, accompanying increases in the nominal wage.

In an attempt to explain the factors responsible for increasing costs in the non-progressive sector, Baumol (1967) model was based on five fundamental premises. The first premise is that economic activities can be grouped into technologically progressive and non-progressive sectors (henceforth, PS and NPS respectively) in terms of different productivity growth rates. Second, the only input is labour. Third, nominal wages in the two sectors are the same and grow at the same rate. The fourth essential axiom is that there is mobility of labour between the two sectors. Lastly, nominal wages will rise with productivity growth in the progressive sector.

Baumol (1967) employs a single factor production function for the goods and services sectors, with labour as the only input. The productivity of labour in the PS is assumed to grow exponentially over time. Productivity growth of labour in the NPS is assumed to be slow or non-existent.

On the basis of the defined axioms, Baumol (1967) derives two theoretical results within the framework of his model. The first is that "the cost per unit of output of the NPS will rise without limit over time, while the unit cost of the PS will remain constant" (Baumol, 1967, p. 418) This result is derived from the combination of rising wages with stagnant productivity in the NPS and from the fact that productivity and wage increases exactly balance each other out so that the unit cost of output in the PS remains constant over time.

A second theoretical result from Baumol's model is that "the labour share of the NPS will increase over time" (Baumol, 1967, p. 418). In the limit, all labour in the economy is employed in the NPS. The result is derived from the assumption that the relative share of outputs in the two sectors remains constant over time. Increased productivity in the PS causes that sector to release labour resources. The equivalence of wages in the two sectors, along with the assumption of perfect labour mobility, implies the result.

In summary, the BCD hypothesises that the health care sector will consume an increasing share of the economy's resources i.e. GDP. Further, it suggests that the increases in costs over time are unavoidable because they are driven by productivity increases outside the health sector (see Baumol, 1967, 1993; Hartwig, 2008b; Towse, 1997). In the words of Baumol (1967), the entire analysis is summarized as "if productivity per man hour rises cumulatively in one sector relative to its rate of growth elsewhere in the economy, while wages rise commensurately in all areas, then relative costs in the non-progressive sectors must inevitably rise, and these costs will rise cumulatively and without limit" (Baumol, 1967, p. 419).

The different presentations of the "Cost Disease" model by Baumol (1967, 1993, 2012) provide a theoretical framework for understanding the increasing size of the health care industry, but are not formulated in such a way as to produce testable hypotheses. Efforts made by other studies to revive and empirically test the hypotheses are reviewed in Section 3.3 However, this thesis argues that these previous attempts (such as Bates & Santerre, 2013; Hartwig, 2008a, 2008b, 2011a, 2011b), suffer from several shortcomings. This motivates my attempt to develop an empirically testable formulation of the BCD model. The model is presented in Section 3.4 below.

3.3 Tests of Baumol's Cost Disease for the Health Sector: Empirical Review

The first application of BCD in the health sector is in the work of Baumol (1993) titled '*Health care, education and the cost disease: A looming crisis for public choice*'. Baumol (1993) descriptively analyses the trend of productivity and total spending in the goods and services sectors in the U.S. He establishes the price implications of the model and concludes that prices in the service sector will continue to rise inevitably due to rising costs and declining labour productivity in the sector. Nixon and Ulmann (2006) expand on this work by studying health expenditures and health outcomes for 15 European Union countries from 1980 to 1995.

The first attempt to empirically test BCD using an estimable model was made by Martins and de la Maisonneuve (2006). They employ a fixed effect panel model for 30 OECD countries from 1981 to 2002. They test the BCD hypothesis by regressing the growth of long-term health expenditures on the growth of labour costs (other explanatory variables such as income and a set of demographic factors). This approach is known as "labour cost" or "wage growth" approach to capture the "Baumol's effect". They report evidence of upward shifts in per capita long-term health expenditures due to a "cost-disease" effect.

Later, Hartwig (2008b) introduces the "wage-productivity growth gap" approach that has been widely cited. This approach uses the difference between economy-wide wage and productivity growth rates to measure "Baumol's effect" to explain rising health spending in OECD countries. In the spirit of Baumol's framework, Hartwig (2008b) approach is based on the logic that if wage increases in the PS reflect productivity increases but wage increases in the NPS are only driven by equalization of wages across sectors (due to a mobile, competitive labour market), then wages in the overall economy will grow faster than overall labour productivity. He employs a simple econometric model to test BCD in the health sector by estimating a Barros (1998) growth model that expresses the health care expenditure (HCE) growth rate as a function of growth in wages and salaries, national output and employment. Hartwig (2008b) finds supporting evidence for BCD in a panel of 19 OECD countries. A similar approach was adopted by later studies[10] such as Colombier (2012, 2017) and Bates and Santerre (2013) for 20 OECD countries and 50 U.S. states, respectively.

However, when replicating Hartwig (2008b) in Chapter 2 of this thesis, key issues relating to theoretical modelling, measurement and hypotheses testing were found and discussed in detail. For instance, Hartwig (2008b) tests the parameter restriction[11] that the coefficient on the "wage-productivity gap" variable is equal to one. He claims that this is a direct test of the "Baumol effect." But the restriction that the coefficient of the wage-productivity growth variable should equal one is nowhere derived from theory. This further supports the point initially made by Colombier (2012, p. 12) that no special attention should be given to the coefficient value of the wage-productivity growth variable and that the BCD hypothesis cannot be confirmed on that basis.

[10] See Table A3.1 in the Appendix for a summary of previous studies examining BCD in the context of the health industry.

[11] Through the replication experiment, I discovered that the parameter restriction tested by Hartwig (2008b, p. 610) does not match the baseline specification algebraically.

Another approach taken by Hartwig for testing BCD in the health sector uses the "output-expenditure growth nexus" (Hartwig (2008a). He reports that increases in health care spending reduce future output growth. This is consistent with the BCD proposition because increases in costs (i.e. health expenditures) mean that resources have shifted to a non-progressive sector with lower productivity growth and, as a consequence, subsequent periods should experience reduced output growth.

Other investigations of the BCD using industry level data include Nordhaus (2008). He provides a comprehensive analysis of "Baumol's effect" using U.S. industry-level data from 1948-2001. Nordhaus (2008) uses multiple model specifications where a set of dependent variables (such as price, nominal output, real output, wages, employment, and profits) are expressed as a function of industry-level productivity. From his approach, the spirit of BCD is immediately apparent as industry-level trends are driven by exogenous technological change. Consistent with BCD, Nordhaus finds that sectors that are relatively technologically stagnant experience rising relative prices and falling relative real outputs and employment. Hartwig (2010, 2011b) extends Nordhaus' approach using Swiss and EU data, respectively.

It is stated in Section 3.2 that Baumol's framework implies that the relative price of services like health care will rise over time with productivity increases in other sectors. Hartwig (2011a) uses this proposition to motivate his study but then focuses on the *consequences*, rather than the *determinants*, of relative price changes. In particular, Hartwig (2011a) employs a "relative medical price" approach and finds that the relative price of health care (used as an explanatory variable) is a significant positive determinant of health care expenditures in the OECD. This is consistent with BCD proposition that rising prices are responsible for the observed rapid health expenditure growth.

It is important to note that while each of the above studies links its empirical specification to the spirit of the BCD framework, in no case have I found an empirical specification, based on a formal theoretical model that is strictly derived from the full set of Baumol's axioms. For example, the "wage-productivity growth gap" approach introduced by Hartwig (2008b) focuses on economy-wide wage growth, productivity growth, and employment growth as exogenous explanatory variables, sometimes combined into a single "Baumol variable". This set up does not directly relate labour migration into the health sector as a response to productivity (and hence wage) increases. Yet, labour migration into health care is one of the key predictions of Baumol's framework.

Similarly, the "relative medical price" approach in Hartwig (2011a) models changes in productivity as a function of exogenous relative health care prices – again ignoring how BCD implies that the relative price of health care is endogenous to productivity. Nordhaus (2008) and Hartwig (2010, 2011a) do not suffer from these endogeneity problems. However, their empirical analysis is again based on the spirit of BCD rather than strictly following Baumol's main propositions. For example, Nordhaus (2008, p. 9) studies six diseases that might be associated with Baumol's analyses, but these are not directly derived from Baumol's propositions. To the best of my knowledge, this thesis is the first to develop a directly-testable theoretical model that is closely related to Baumol (1967) framework. The next section presents this theoretical model.

3.4 A Theoretical Model for Testing Baumol's Cost Disease

On the basis of the above-discussed theoretical gap, my study develops Baumol (1967) model to allow direct empirical testing. Like Baumol, I start with a two-sector economy consisting of a technologically progressive sector (representing the non-health sector) and a stagnant sector (representing the health industry). For the purposes of this analysis, the two sectors are respectively referred to as the health (H) and non-health (NH) sectors. Also like Baumol, I assume that the only input to production is labour. The production functions for the two sectors are given by:

$$Y_{NH} = \phi L_{NH} \tag{3.1}$$

$$Y_H = L_H \tag{3.2}$$

where ϕ is labour productivity in the non-health sector; L_{NH} and L_H are the amounts of labour employed in the non-health and health sectors; and Y_{NH} and Y_H are the associated real outputs. Also, ϕ represents relative labour productivities in the *NH* and *H* sectors, with $\phi > 1$ indicating greater productivity in the *NH* sector.

A key assumption is that output in both sectors is a constant share of total output in the economy, *Y* (Baumol, 1967, p. 419). Define *k* as the share of total economy output accounted for by the non-health sector:

$$Y_{NH} = kY \tag{3.3}$$

Demand equals supply in the NH sector implies that:

$$kY = \phi L_{NH} \tag{3.4}$$

so that the amount of labour employed in the NH sector is given by:

$$L_{NH} = \left(\frac{k}{\phi}\right) Y \tag{3.5}$$

Total labour supply is given by *L*, so that

$$L_H + L_{NH} = L \ . \tag{3.6}$$

It follows from Equations (3.1), (3.2) and (3.5) that

$$L_{NH} = \left(\frac{k}{\phi}\right) Y = \left(\frac{k}{\phi}\right)\left(\phi L_{NH} + L_H\right) \tag{3.7}$$

Equations (3.6) and (3.7) constitute two equations in two unknowns, L_H and L_{NH}, as functions of ϕ, k, and *L*. This allows one to solve for L_H and L_{NH} as:

$$L_{NH} = kL_{NH} + \left(\frac{k}{\phi}\right) L_H \tag{3.8}$$

$$(1-k)L_{NH} = \left(\frac{k}{\phi}\right) L_H \tag{3.9}$$

$$L_{NH} = \left[\frac{k}{(1-k)\phi}\right] L_H \tag{3.10}$$

Also,

$$L_H = L - \left[\frac{k}{(1-k)\phi}\right] L_H \tag{3.11}$$

$$L_H + \left[\frac{k}{(1-k)\phi}\right] L_H = L \tag{3.12}$$

$$\left[\frac{(1-k)\phi + k}{(1-k)\phi}\right] L_H = L \tag{3.13}$$

$$L_H = \left[\frac{(1-k)\phi}{((1-k)\phi + k)}\right] L \tag{3.14}$$

The two sector shares of the labour force are given by:

$$\frac{L_H}{L} = \left[\frac{(1-k)\phi}{((1-k)\phi + k)}\right] \tag{3.15}$$

Equation (3.15) implies that the health sector share of the labour force is positively related to productivity in the *NH* sector (ϕ) and the health sector share of national output $(1-k)$.

Also,

$$\frac{L_{NH}}{L} = \left[\frac{k}{((1-k)\phi + k)}\right] \tag{3.16}$$

from (3.15) and (3.16), it can be confirmed that (i) when $k = 1$, $\frac{L_{NH}}{L} = 1$ and $\frac{L_H}{L} = 0$; and (ii) when $k = 0$, $\frac{L_{NH}}{L} = 0$ and $\frac{L_H}{L} = 1$.

Further,

$$\frac{\partial\left(L_H/L\right)}{\partial\phi} = \frac{\partial\left([(1-k)\phi]\cdot[((1-k)\phi+k)]^{-1}\right)}{\partial\phi} =$$

$$= \frac{(1-k)}{[(1-k)\phi+k]} - \frac{(1-k)^2\phi}{[(1-k)\phi+k]^2}$$

$$= \frac{(1-k)}{[(1-k)\phi+k]}\cdot\left[1-\frac{(1-k)\phi}{([(1-k)\phi+k])}\right].$$

From Equation (3.15):

$$= \frac{(1-k)}{[(1-k)\phi+k]}\cdot\left[1-\frac{L_H}{L}\right]$$

$$= \left(\frac{L_{NH}}{L}\right)\cdot\frac{(1-k)}{[(1-k)\phi+k]} \tag{3.17}$$

It is easily determined that both terms on the right hand side of Equation (3.17) are positive, so that

$$\frac{\partial\left(L_H/L\right)}{\partial\phi} > 0 \tag{3.18}$$

Let w_{NH} and P_{NH} be the market wage and price level in the *NH* sector. The marginal product of labour in the non-health sector is given by:

$$MPL_{NH} = \frac{\partial Y_{NH}}{\partial L_{NH}} = \phi \tag{3.19}$$

It is assumed that workers are paid their marginal product in the non-health sector, so

$$MPL_{NH} = \left(\frac{w_{NH}}{P_{NH}}\right) = \phi\,,$$

(3.20)

where P_{NH} is the price of the non-health sector good. So that:

$$w_{NH} = MPL_{NH}\cdot P_{NH} = \phi\cdot P_{NH} \tag{3.21}$$

Equilibrium in the labour market requires workers in the *H* and *NH* sectors to be paid the same:

$$w_H = w_{NH} = \phi \cdot P_{NH} \tag{3.22}$$

Given the constant returns-to-scale production in the non-health sector, profits in this sector are given by

$$\pi_{NH} = P_{NH}Y_{NH} - w_{NH}L_{NH} = P_{NH}kY - \phi P_{NH}\left(\frac{k}{\phi}\right)Y = 0 \tag{3.23}$$

Profits in the health sector are given by

$$\pi_H = P_H Y_H - w_H L_H = P_H L_H - w_H L_H = (P_H - w_H)L_H \tag{3.24}$$

If the condition that a competitive equilibrium in the health sector drives profits to zero[12] is imposed, then it follows that $P_H = w_H$, and, from Equation (3.22),

$$P_H = \phi \cdot P_{NH} \qquad (3.25)^{13}$$

In terms of relative prices, (3.25) can be expressed as a function of productivity in the non-health sector as:

$$\frac{P_H}{P_{NH}} = \phi \tag{3.26}$$

and it is obvious that

$$\frac{\partial (P_H / P_{NH})}{\partial \phi} > 0 \tag{3.27}$$

The preceding analysis has given two key implications of BCD:

[12] This is also consistent with the view of Newhouse (1970) that the health sector is dominated by not-for-profit firms whose administrators or managers maximise quality and quantity subject to a break-even constraint. Pauly (1987), on the other hand, argues that non-profit institutions like hospitals still de facto make profit which is then paid out in form of dividends to decision makers such as the administrator and physicians. In this latter view, non-profit firms seek to maximize the money income of decision making agents.

[13] This expresses a simplified health care price model dependent on labour productivity in the progressive sector or the equilibrium wage rate and general price of other goods in the economy. In relative prices as shown in (3.26), the expression captures the Baumol's effect. This is similar to Hartwig (2008b, 2011a) and Colombier (2012, 2017) argument that the essence of testing for the Baumol's effect is to examine the impact of health price increases on health expenditure. Considering the measurement shortcomings of constructing a reliable medical price index as emphasized by Cutler et al. (1998), Baumol's variable is seen as a proximate measure to capture the effect.

(i) $\dfrac{\partial(L_H/L)}{\partial\phi} > 0$ (from Equation 3.18)

(ii) $\dfrac{\partial(P_H/P_{NH})}{\partial\phi} > 0$ (from Equation 3.27)

The economic intuition underlying these hypotheses is as follows: Productivity increases in the non-health sector cause fewer workers to be needed in this sector. As a result, workers are released to the heath sector and the health sector share of the labour force increases. At the same time, higher productivity in the non-health sector raises wages there. Equilibrium in the labour market causes these wage increases to spill over to the health sector. The resulting higher costs of production in the health sector drive up prices, so that the ratio of prices in the health and non-health sectors also rises.

If the parameter, ϕ , which measures productivity in the non-health sector, were observable, then the inequalities above would provide testable hypotheses of BCD, as both (L_H/L) -- the share of labour employed in the health sector -- and (P_H/P_{NH})-- the relative price indices of output in the health and non-health sectors – are not difficult to obtain. However, ϕ is frequently unobserved, or non-comparable, especially when working with cross-country data. Therefore, the two consequences of the BCD model are reformulated in terms of economy-wide productivity, *PROD*, which is observable.

Define economy-wide productivity as

$$PROD \equiv \frac{Y}{L} \tag{3.28}$$

Note that economy-wide productivity is a weighted average of productivity in the *NH* and *H* sectors,

$$PROD = \frac{Y}{L} = \phi\left(\frac{L_{NH}}{L}\right) + \left(\frac{L_H}{L}\right), \tag{3.29}$$

and that both $\left(\frac{L_{NH}}{L}\right)$ and $\left(\frac{L_H}{L}\right)$ are functions of ϕ (from Equations 3.15 and 3.16). Thus

$PROD = f(\phi)$ and

$$\phi = f^{-1}(PROD) \tag{3.30}$$

It is feasible to demonstrate that:

(i) $$\frac{\partial (L_H/L)}{\partial PROD} = \frac{\partial (L_H/L)}{\partial \phi} \cdot \frac{\partial \phi}{\partial PROD} > 0$$

(ii) $$\frac{\partial (P_H/P_{NH})}{\partial PROD} = \frac{\partial (P_H/P_{NH})}{\partial \phi} \cdot \frac{\partial \phi}{\partial PROD} > 0 .$$

To prove the above, it is sufficient to show that $\frac{\partial \phi}{\partial PROD}$ > 0.

$$\begin{aligned} PROD &= \phi\left(\frac{L_{NH}}{L}\right) + \left(\frac{L_H}{L}\right) \\ &= \phi\left(1 - \frac{L_H}{L}\right) + \left(\frac{L_H}{L}\right) \\ &= \phi - (\phi - 1)\frac{L_H}{L} \end{aligned} \tag{3.31}$$

$$\frac{\partial PROD}{\partial \phi} = 1 - \left(\frac{L_H}{L}\right) - (\phi - 1) \cdot \frac{\partial \left(L_H / L\right)}{\partial \phi} \tag{3.32}$$

$$\frac{\partial PROD}{\partial \phi} = \left(\frac{L_{NH}}{L}\right) - (\phi - 1) \cdot \frac{\partial \left(L_H / L\right)}{\partial \phi} \tag{3.33}$$

Substituting (3.17) into (3.33) yields

$$\begin{aligned} \frac{\partial PROD}{\partial \phi} &= \left(\frac{L_{NH}}{L}\right) - (\phi - 1) \cdot \left(\frac{L_{NH}}{L}\right) \cdot \frac{(1-k)}{[(1-k)\phi + k]} \\ &= \left(\frac{L_{NH}}{L}\right) \cdot \left\{1 - (\phi - 1) \cdot \frac{(1-k)}{[(1-k)\phi + k]}\right\} \end{aligned}$$

$$= \left(\frac{L_{NH}}{L} \right) \cdot \left\{ \frac{(1-k)\phi + k}{[(1-k)\phi + k]} - (\phi - 1) \cdot \frac{(1-k)}{[(1-k)\phi + k]} \right\}$$

$$= \left(\frac{L_{NH}}{L} \right) \cdot \left\{ \frac{1}{[(1-k)\phi + k]} \right\} \tag{3.34}$$

It is easily determined that both terms on the right hand side of Equation (3.34) are positive, so that

$$\frac{\partial PROD}{\partial \phi} > 0 \tag{3.35}$$

and, from Equation (30), it follows that

$$\frac{\partial \phi}{\partial PROD} > 0 \tag{3.36}$$

The above analysis yields the following testable implications of BCD:

(i) $$\frac{\partial (L_H / L)}{\partial PROD} > 0 \tag{3.37}$$

(ii) $$\frac{\partial (P_H / P_{NH})}{\partial PROD} > 0 \tag{3.38}$$

In words, Equations (3.37) and (3.38) state that (i) the share of labour employed in the health sector (L_H / L) and (ii) the price index of goods produced in the health sector relative to the price index of goods produces in the non-health sector (P_H / P_{NH}) should both be increasing functions of economy-wide productivity.

The above model incorporates all the five properties that characterise Baumol (1967) cost disease framework in that: (i) the economy consists of two sectors: a technologically progressive sector, and a technologically stagnant sector; (ii) labour is the only input into production; (iii) wages in the two sectors grow at the same rate; (iv) labour is perfectly mobile between the two sectors; and (iv) nominal wages rise with productivity growth in the progressive sector. The BCD characteristics are used to generate hypotheses that are testable with observable data.

Further, the hypotheses given by expressions (3.37) and (3.38) are sufficiently specific, and not obviously consistent with alternative theories, that they are strong candidates for testing whether BCD can explain rising health care costs across countries.

3.5 Methods

3.5.1 Data Description, Sources and Sample

The variables required for this study are: the health price index, overall consumer price index, GDP in current prices, total number of hours worked, health sector employment, and total labour force. Other explanatory variables that are commonly considered in explaining rising health spending in previous studies are also used. These include the age and gender composition of the population, health outcomes (life expectancy at birth and infant mortality), health-related behaviour (tobacco and alcohol consumption per capita), and economic growth.

Also, using a precise measure of non-health prices is an improvement over previous studies which rely on the GDP deflator instead (e.g., Hartwig, 2008a; Hartwig, 2008b, 2011a). Productivity is measured as the ratio of real GDP to the number of hours worked.

It is difficult to obtain a comprehensive and consistent data set with health care prices for all OECD countries. Fortunately, the EUROSTAT 2014 Online Database contains data for many OECD countries. All other variables are sourced from OECD Health Statistics, 2014. The final sample covers the years 1995 to 2013 and includes data for 27 out of 34 OECD countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the U.S.

3.5.2 Trend and Descriptive Analyses

To visualise our data, Figure 3.2 shows time series plots for productivity and the share of employment in the health sector for selected OECD countries over the years 1995-2013.

LHSL represents $\frac{L_H}{L}$. Generally, the plots show increasing trends of health sector labour shares as predicted by BCD. However, there is considerable variation across countries.

The corresponding plot for productivity and relative prices, where *PHN* represents P_H / P_{NH}, is shown in Figure 3.3. Again, there is substantial variation across countries. In some countries, relative health care prices increased (Austria, France, Norway, Spain, Switzerland and Turkey), in others they fluctuated (Denmark, Germany, Greece, Iceland, Netherlands, Portugal, Sweden, and United Kingdom), and in some countries they even declined (Finland, and Italy).

Figure 3.2: Plot of Health Sector Share of Labour Force vs. Productivity for selected OECD Countries

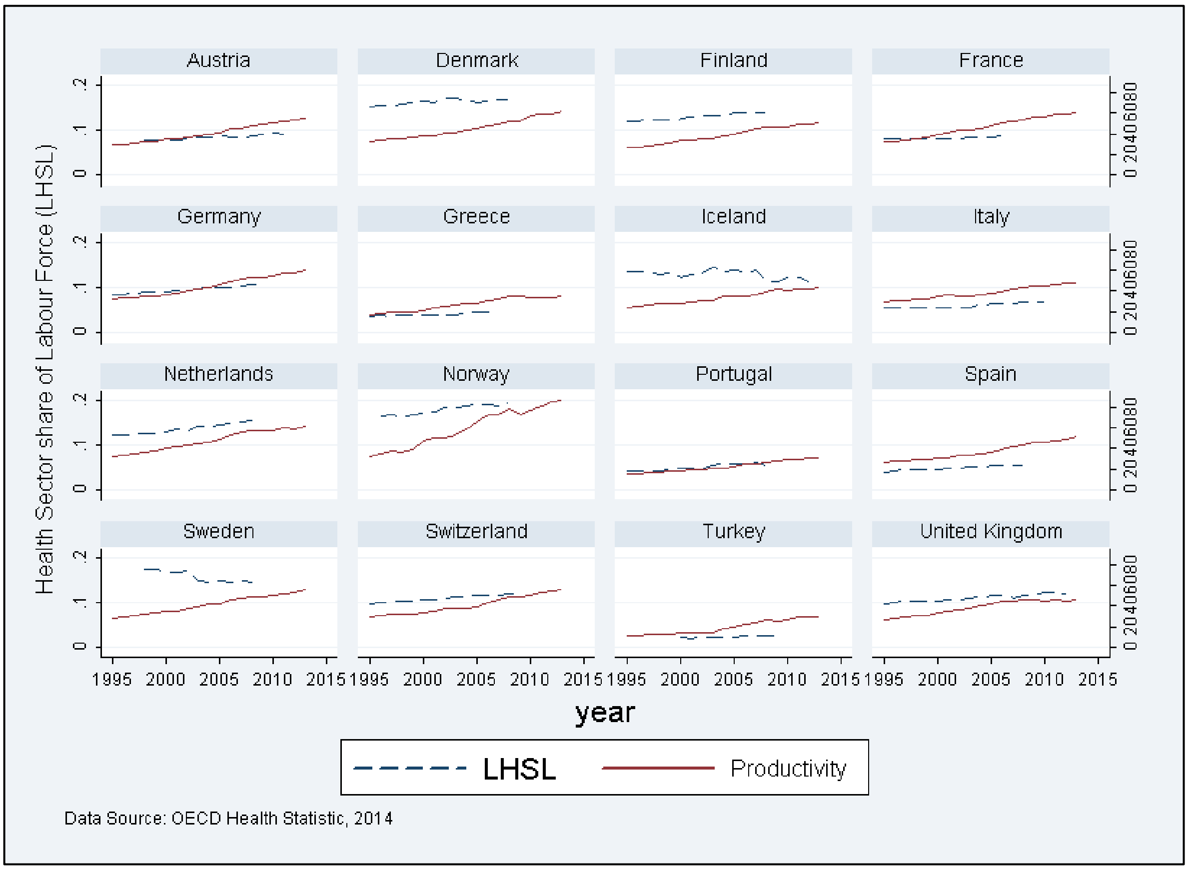
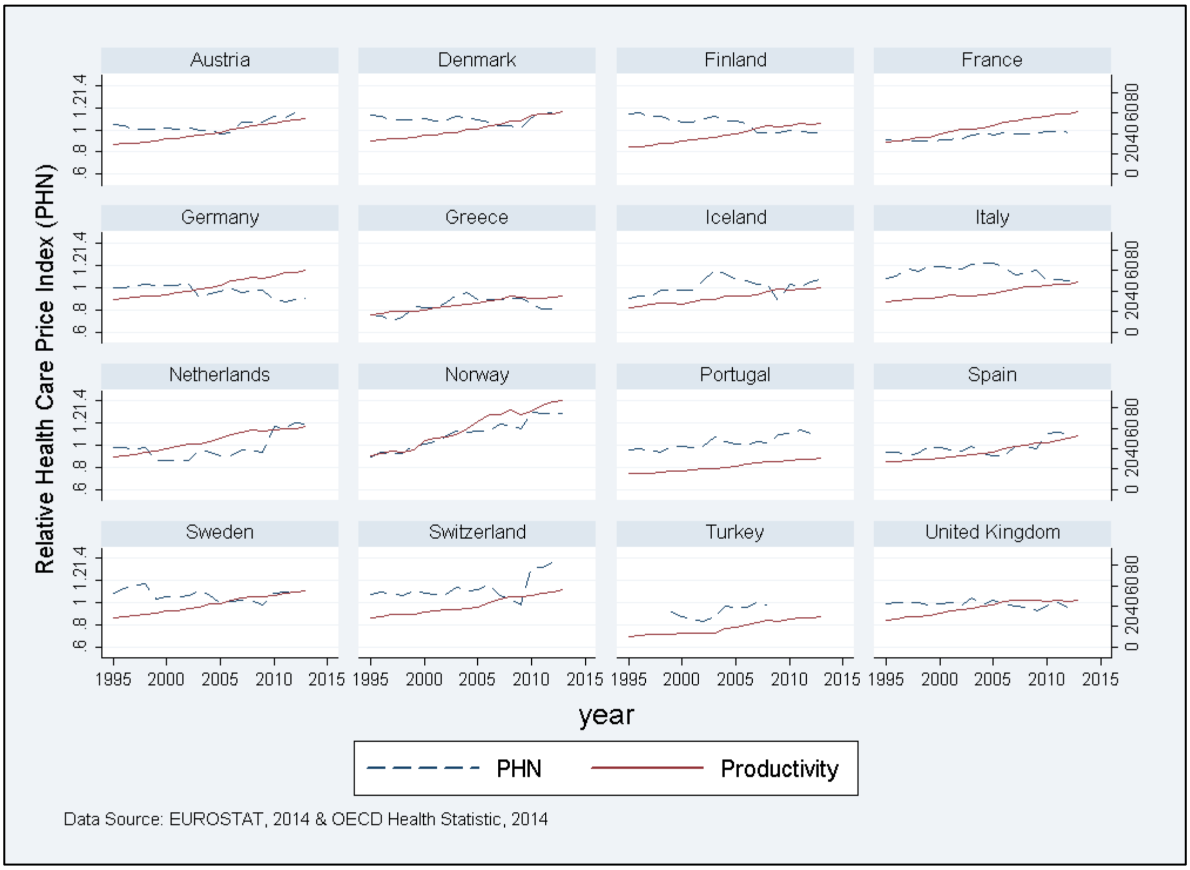


Figure 3.3: Plot of Relative Health Care Price Index vs. Productivity for selected OECD Countries



Overall, the plots of productivity measured by the ratio of GDP to the number of hours worked show increasing trends over time excluding the period of the global financial crisis (see Figures 3.2 and 3.3). The trend analysis indicates the need to incorporate country fixed effects and a time trend.

The trend analysis seems to support the BCD but it is an unreliable and insufficient method of testing the formulated hypotheses. The next sub-sections discuss the methods employed to formally test the BCD hypotheses.

The summary statistics of the variables used in testing the BCD hypotheses are reported in Table 3.1. The demographic and health variables display much variation across countries. For example, the share of the population older than 64 years ranges from 5.4% (Turkey) to 21.1% (Germany). The minimum life expectancy at birth in our sample is 67.9 (Estonia), and the maximum is 83.2 (Spain), with a mean of 78.5.

Table 3.1: Descriptive Statistics

Variable	Obs	Mean	Std Dev	Min	Max
Ratio of prices in the health and non-health sectors (*PHN*)	383	99.66	14.15	55.58	142.6
Health sector share of the labour force (*LHSL*)	392	9.94	4.09	2.15	20.13
Productivity (*PROD*)	506	38.31	14.30	10.76	86.85
Population < 15 years (% of total)	513	18.0	3.1	12.9	32.1
Population > 64 years (% of total)	513	15.0	2.7	5.4	21.1
Male population (% total)	513	49.0	0.8	46.1	51.1
Life expectancy at birth (in years)	511	78.5	2.8	67.9	83.2
Infant mortality (per 1,000 live births)	507	5.2	4.2	0.9	40.9
Tobacco consumption (grams per capita ≥ 15 years)	328	1758	603	557	3741
Alcohol consumption (litres per capita ≥ 15 years)	491	9.9	2.7	1.2	15.1
GDP growth rate (%)	509	2.4	3.0	-14.7	11.7

NOTE: The sample consists of annual data for years 1995-2013 from 27 OECD countries: Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, and U.S. *PHN* is calculated using the health price index and the overall consumer price index. *LHSL* is the fraction of the total labour force employed in the health sector. *PROD* is measured as the ratio of GDP to the number of hours worked.

Table 3.2: Pre-Estimation Diagnostics Test Results

Variable	Pesaran (2004) CD Test		Maddala & Wu (1999) PURT				Pesaran (2007) CIPS PURT			
			Level		FD		Level		FD	
	CD_{PES}	$\lvert\bar{\hat{\rho}}\rvert$	No Trend	Trend	No Trend	Trend	No Trend	Trend	No Trend	Trend
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(LHSL)	27.77***	0.649	1	1	0***	0***	1	1	0**	1
PHN	4.35***	0.431	1	1	0***	0***	1	1	0***	1
PROD	48.85***	0.980	1	1	0***	0***	1	1	0***	1
Age < 15	63.18***	0.808	0***	0***	1	1	1	1	1	1
Age > 64	57.58***	0.741	1	0***	0***	0***	1	1	1	1
Male	21.26***	0.626	1	0***	0***	0***	0*	0**	0***	1
ln(Life expectancy)	76.54***	0.980	1	1	0***	0***	1	1	0***	0***
ln(Infant mortality)	66.64***	0.853	1	0**	0***	0***	1	1	0***	0***
ln(Tobacco consumption)	-	-	-	-	0***	0***	-	-	0***	1
ln(Alcohol consumption)	4.46***	0.527	1	1	0***	0***	1	1	0***	0***
GDP growth rate	52.35***	0.646	0***	0***	0***	0***	0**	1	0***	0***

NOTE: CD = Cross-sectional dependence; PURT = Panel Unit Root Test; CIPS = Cross-sectional augmented Im, Pesaran, and Shin (2003); FD = First Difference; $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series; CD_{PES} = Pesaran (2004) CD test; Null hypothesis for Maddala and Wu (1999) and Pesaran (2007) CIPS tests is "no stationarity" i.e. series is I(1); MW test assumes cross-section independence; CIPS test assumes cross-sectional dependence in form of a single unobserved common factor; "-" = Insufficient observation [Spain has only 2 observations]. * 10%, ** 5%, and *** 1% significance level respectively; 1 = No stationary i.e. the series is I(1); 0 = Stationary i.e. the series is I(0). Lag 1 is used for all the PURTs. The results for logged and unlogged forms of PROD, PHN, Age < 15, Age > 64 and Male are identical qualitatively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Infant mortality ranges from 0.9 per 1,000 live births (Iceland) to 40.9 (Turkey). There are also wide differences in lifestyle behaviours that can impact health outcomes. The minimum tobacco consumption in our sample is 557 grams per person (Finland), with a maximum value of 3,741 grams per person (Greece). Alcohol consumption ranges from 1.2 litres per person (Turkey), to a maximum of 15.1 litres per person (France).

3.5.3 Pre-Estimation Diagnostic Tests

The estimation strategy and robustness checks adopted in this chapter prompt the need to investigate the existence and size of cross-sectional correlation of considered variables prior to estimation. The cross-sectional correlation of panel series across countries might emanate from unobservable common macroeconomic shocks (De Hoyos & Sarafidis, 2006). If each of the series is cross-sectionally dependent, standard panel data estimators (such as pooled ordinary least squares (POLS), cross-section fixed effect (CFE), time fixed effect (TFE), and two-way fixed effect (2WFE)) might produce misleading inference and inefficient estimates (Chudik & Pesaran, 2013; Sarafidis & Wansbeek, 2012).

Pesaran (2004) cross-sectional dependence test is used to investigate the correlation of the variables across countries. The method is chosen for its robustness and application to unbalanced panel data that is used in this chapter. The method tests the null hypothesis of "no cross-sectional dependence".

Also, the stationarity properties of the time series variables are examined using the first (Maddala and Wu (1999); henceforth MW) and second (Pesaran (2007); cross-sectional augmented Im et al. (2003); henceforth CIPS) generation of panel unit-root tests (PURT) (see Baltagi, 2013 for more discussion). The two tests have a null hypothesis of "non stationarity".

3.5.4 Estimation Methods

This study starts estimating the theoretical BCD predictions of Equation (3.37) and (3.38) using standard panel data estimators. This includes POLS, 2WFE, and FE with country-specific linear time trends.

For the diagnostic checks, the cross-sectional correlation and stationarity of the residuals from the standard panel data estimators are examined. The methods considered for the pre-estimation diagnostic tests are similarly used for the post-estimation tests. To account for estimation issues such as serial correlation, cross-sectional dependence and non-stationarity when identified, robust panel estimators are employed. The estimators include: Panel-Corrected Standard Error (PCSE); Mean Group (MG); Common Correlated Effects Mean Group (CCEMG); and the Augmented Mean Group (AMG) estimators.

3.6 Results and Discussion

As discussed above, the cross-sectional dependence test and panel unit root test are used to evaluate the properties of the variables for examining the BCD predictions expressed in Equations (3.37) and (3.38). Table 3.2 reports the results of the Pesaran (2004) CD test (Columns 1 and 2), Maddala and Wu (1999) PURT (Columns 3 to 6), and Pesaran (2007) PURT (Columns 7 to 10). The null hypothesis of “cross-sectional independence” is rejected at the 1% significance level for all the variables used for testing the BCD hypothesis. Most of the panel variables excluding the ratio of prices in the health and non-health sectors (PHN) show high levels of cross-sectional correlation with coefficients ranging from 0.528 (log of alcohol consumption) to 0.982 (log of life expectancy).

The PURT diagnostic results in Table 3.2 indicate slight differences between the PURT methods for trend and no trend specifications when level and first difference series are considered. The consistent I(0) results are highlighted in yellow. At level, it is clear that population aged less than 15 and GDP growth rate are the only stationary variables using

Maddala and Wu (1999) PURT, while the proportion of male population is found stationary using Pesaran (2007) PURT. Using CIPS to test account for cross-sectional dependence issue, only life expectancy, infant mortality, alcohol consumption and GDP growth rate are found to be stationary at first difference. Similarly, Maddala and Wu (1999) PURT (Columns 5 and 6 of Table 3.2) also confirms the non-stationarity of those series at level, i.e. for all the panel units, the variables are integrated of order one.

Table 3.3 reports the effect of productivity on the health sector share of the labour force (LHSL) as a first test of the BCD hypothesis. The POLS, 2WFE, and FE with country specific linear time trends are the baseline estimation methods employed to estimate three different specifications of Equation (3.37). The first specification controls for age and gender demographic factors with productivity. Tobacco and alcohol consumption as lifestyle measures are incorporated in the second specification. Economic growth (GDP growth rate) is included as an additional control variable in the last specification to control for possible omitted variable bias that may arise from the effect economic growth may have on the economy's prices and input allocations.

The results of the diagnostic tests after estimating each of the specifications are reported in the bottom rows of Table 3.3. One of the tests is a test of joint significance of country and time effects in specifications estimated by 2WFE and FE with individual country time trends. For instance, the F statistic value in column (4), 209.21, is significant at the 1% critical level. This indicates that the country and time effects significantly drive variation in the health sector share of the labour force (LHSL). The Bayesian Information Criterion (BIC) is another diagnostic measure used to evaluate country and time effects. BIC allows specification comparison across regressions, with lower values indicating "better" specifications according to this diagnostic. For example, the regression results in Columns (3) and (6) have identical specifications except that Column (6) includes fixed effects for country and year. The BIC value in Column (3) is 14.54, compared to a value of -668.3 in Column (6). This indicates that country and year fixed effects add valuable explanatory power to the specification. Also, the Ramsey Regression Equation Specification Error Test (RESET) is included to test if the respective estimated equation is correctly specified. The test procedure involves regression of the endogenous variables on a non-linear combination of its predicted values and the original regressors. The joint significance of the predicted value estimates is evaluated using an F-test with the null hypothesis of "no specification error". Rejection indicates misspecification.

The reported results in Columns (1) to (6) for specifications estimated using POLS and 2WFE reveal a positive relationship between productivity (PROD) and LHSL. The coefficient on the productivity variable is generally highly significant, with *p*-values less than 0.01 in all but one of the regressions. This result provides support for the BCD hypothesis. However, superior analyses based on diagnostics tests (BIC and RESET) support inclusion of country-specific linear time trends and indicate no support for the BCD hypothesis. The results for the FE with country specific time trend indicate a negative and insignificant effect of PROD on LHSL. This indicates no support for the BCD hypothesis.

The justification for the inclusion of country-specific time trends is to control for common trending behaviour as reported in section 3.5.2. The country and time effects included in the specification (Columns 7 to 9) are jointly significant with reported p-values less than 0.001. The BIC results also show stronger support for the FE with country-specific time trends compared with POLS and 2WFE. For example, Column (9) has a BIC value of -806.0 compared to -668.3 in Column (6), indicating that country fixed effects with country-specific time trends provide a better fit than country and year fixed effects, even after penalizing for the inclusion of additional variables. Lastly, the RESET fails to reject the null hypothesis of "no specification error" in two of the three models including country-specific time trends (Columns

7 and 9). In contrast, specification error was found in all the reported results for POLS and 2WFE (Columns 1 through 6).

The results reported in Table 3.3 also reveal robustness of the specifications to the inclusion of control variables (age and demographic factors; lifestyle variables; and economic growth). The control variables are found significant in some specifications but have little effect on the relationship between PROD and LHSL, even in the preferred specifications (Columns 7 to 9) where negative and insignificant estimates are reported. This provides sufficient evidence to conclude that the BCD prediction of Equation (3.37) is not supported by my analysis.

The reported results for testing the BCD prediction of Equation (3.38) in Table 3.4 are similar qualitatively to the findings from Table 3.3. The results provide estimates of the relationship between productivity and the ratio of prices in the health and non-health sectors (PHN).[14] As earlier reported in Table 3.3, productivity estimates from POLS and 2WFE in Table 3.4 also indicate a positive and significant effect and provide evidence in support of BCD hypothesis. However, the coefficient on the productivity variable turns from positive and generally significant in Columns (1) through (6), to negative and statistically insignificant in Columns (7) through (9). Similarly, post-estimation diagnostic tests (such as the joint significance of country and time effects, BIC and RESET) indicate the robustness of the FE with country-specific time trends specification (Columns 7 to 9, Table 3.4). The robustness specifications are preferred and the results provide no evidence to support the BCD hypothesis when the prediction of Equation (3.38) is tested.

The preceding results that provide no support for BCD hypothesis could potentially be biased due to econometric issues such as cross-sectional dependence, non-stationarity, serial

[14] Unlike the specifications in Table 3.3, none of the variables in Table 3.4 are logged. This time the RESET results preferred the unlogged versions of the respective variables. However, the conclusions regarding the significance of the productivity variables were qualitatively identical between the two tables.

Table 3.3: First Test of the BCD Hypothesis: Health Sector Share of the Labour Force (*LHSL*)

Variable	POLS			2WFE			FE with Country-Specific Time Trends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PROD	0.5607*** (9.03)	0.6245*** (9.84)	0.6282*** (9.72)	0.0901 (1.32)	0.1993*** (3.37)	0.1991*** (3.34)	-0.0471 (-0.54)	-0.0467 (-0.64)	-0.0794 (-1.09)
Age < 15	0.0990*** (8.63)	0.0714*** (6.07)	0.0711*** (5.94)	0.0155** (2.06)	0.0053 (0.75)	0.0057 (0.80)	0.0147 (1.37)	0.0385*** (4.03)	0.0394*** (4.16)
Age > 64	0.0799*** (5.54)	0.0852*** (6.51)	0.0858*** (6.50)	-0.0048 (-0.69)	0.0047 (0.62)	0.0038 (0.49)	-0.0066 (-0.47)	-0.0046 (-0.36)	-0.0037 (-0.30)
Male	0.0126 (0.33)	0.1158** (2.43)	0.1200** (2.49)	-0.1093*** (-3.53)	-0.0610** (-2.26)	-0.0634** (-2.32)	-0.0780** (-2.19)	-0.0394 (-1.37)	-0.0350 (-1.22)
ln(Life expectancy)	-2.1007** (-2.10)	-5.4472*** (-5.93)	-5.5594*** (-5.96)	3.4223*** (3.47)	5.5085*** (5.20)	5.5502*** (5.21)	-1.2405 (-1.21)	1.0207 (1.03)	0.5893 (0.59)
ln(Infant mortality)	-0.4804*** (-8.42)	-0.5612*** (-9.65)	-0.5614*** (-9.61)	0.0602 (2.20)	0.0133 (0.44)	0.0119 (0.39)	0.0048 (0.18)	-0.0062 (-0.22)	-0.0066 (-0.24)
ln(Tobacco consumption)	----	-0.3050*** (-5.36)	-0.3125*** (-5.43)	----	-0.0857** (-2.45)	-0.0884** (-2.50)	----	-0.1022*** (-2.64)	-0.0960** (-2.47)
ln(Alcohol consumption)	----	0.1699*** (3.43)	0.1704*** (3.38)	----	-0.1911*** (-3.49)	-0.1925*** (-3.47)	----	-0.0536 (-0.93)	-0.0694 (-1.22)
GDP growth rate	----	----	0.0018 (0.30)	----	----	0.0013 (0.75)	----	----	0.0029*** (2.75)
Obs.	384	258	256	384	258	256	384	258	256
N	27	19	19	27	19	19	27	19	19
Adj. R^2	0.534	0.749	0.749	0.981	0.991	0.991	0.988	0.995	0.995
Country and time effects	----	----	----	*F*=209.2***	*F*=180.1***	*F*=177.4***	*F*=280.1***	*F*=297.1***	*F*=301.9***

Variable	POLS			2WFE			FE with Country-Specific Time Trends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BIC	214.4	8.393	14.54	-808.4	-681.3	-668.3	-947.2	-812.1	-806.0
RESET	12.96 (*p=0.000*)	20.90 (*p=0.000*)	21.10 (*p=0.000*)	*F*=14.96 (*p=0.000*)	*F*=4.98 (*p=0.002*)	*F*=5.41 (*p=0.001*)	*F*=2.06 (*p=0.105*)	*F*=3.51 (*p=0.016*)	*F*=1.58 (*p=0.196*)
Serial Correlation	----	----	----	----	----	----	*F=50.49****	*F=28.89****	*F=26.14****
Pesaran's CD test	----	----	----	----	----	----	*z=11.447****	----	----
CIPS PURT (Error term)	I(1)	----	----	I(1)	----	----	I(1)	----	----

NOTE: The dependent variable is ln(*LHSL*). "POLS", "2WFE" and "FE with Country-Specific Time Trends" stand for OLS regression without fixed effects, OLS regression with fixed effects for country and year, and OLS regression with fixed effects for country and country-specific linear time trends. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. Unless otherwise indicated, numbers in parentheses report cluster-robust standard errors, with clustering by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.4: Second Test of the BCD Hypothesis: Ratio of Prices in the Health and Non-Health Sectors (*PHN*)

Variable	POLS			2WFE			FE with Country-Specific Time Trends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PROD	0.3110*** (6.17)	0.1134 (1.28)	0.1455 (1.64)	0.8570*** (6.96)	1.0112*** (6.50)	1.0045*** (6.37)	-0.1587 (-0.81)	-0.2335 (-0.96)	-0.1931 (-0.79)
Age < 15	0.1566 (0.37)	0.0323 (0.05)	0.0434 (0.07)	-3.8538*** (-4.52)	-5.8166*** (-4.37)	-5.7151*** (-4.26)	-3.1860*** (-2.97)	-2.9458 (-1.53)	-2.6804 (-1.39)
Age > 64	-0.4720 (-0.92)	0.1725 (0.25)	0.2915 (0.42)	-2.5627*** (-3.74)	-4.0438*** (-4.18)	-3.9622*** (-4.04)	3.0640*** (3.17)	2.8439* (1.94)	3.0153** (2.05)
Male	0.9809 (0.84)	7.2082*** (3.50)	7.3550*** (3.60)	-13.334*** (-5.00)	-14.271*** (-3.22)	-14.767*** (-3.28)	-4.8124 (-1.52)	-8.8371** (-1.99)	-8.8307** (-1.98)
Life expectancy	2.5511*** (5.83)	1.7411*** (3.05)	1.6824*** (2.96)	4.4834*** (4.41)	-0.5052 (-0.24)	-0.7730 (-0.36)	2.7175** (2.14)	1.7882 (1.06)	1.4402 (0.84)
Infant mortality	0.3431 (1.48)	0.1989 (0.68)	0.2549 (0.88)	1.1137*** (3.82)	0.8503 (2.41)	0.8624** (2.41)	0.0413 (0.07)	-1.7417*** (-2.60)	-1.7196** (-2.58)
Tobacco consumption	----	-0.0057*** (-3.52)	-0.0060*** (-3.75)	----	0.0011 (0.39)	0.0008 (0.26)	----	-0.0021 (-0.71)	-0.0027 (-0.90)
Alcohol consumption	----	0.3770 (0.98)	0.4355 (1.14)	----	-0.7409 (-0.89)	-0.6231 (-0.74)	----	3.1489*** (3.46)	2.9972*** (3.25)
GDP growth rate	----	----	0.5625** (2.04)	----	----	0.0983 (0.35)	----	----	0.1812 (1.25)
Obs.	382	215	213	382	215	213	382	215	213
N	21	14	14	21	14	14	21	14	14
Adj. R^2	0.452	0.426	0.442	0.799	0.796	0.795	0.856	0.879	0.880
Country and time effects	----	----	----	F=18.09***	F=13.05***	F=12.32***	F=26.75***	F=29.48***	F=28.42***

Variable	POLS			2WFE			FE with Country-Specific Time Trends		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BIC	2904.3	1648.4	1632.5	2705.5	1557.5	1549.5	2592.4	1429.0	1419.6
RESET	F=21.32 (p=0.000)	F=13.04 (p=0.000)	F=10.03 (p=0.000)	F=7.57 (p=0.000)	F=2.01 (p=0.114)	F=2.26 (p=0.084)	F=1.90 (p=0.130)	F=2.53 (p=0.059)	F=1.92 (p=0.128)
Serial Correlation	----	----	----	----	----	----	*F=179.54****	*F=39.28****	*F=41.19****
Pesaran's CD test	----	----	----	----	----	----	*z=3.646****	----	----
CIPS PURT (Error term)	I(1)	----	----	I(1)	----	----	I(1)	----	----

NOTE: The dependent variable is *PHN*. "POLS", "2WFE" and "FE with Country-Specific Time Trends" stand for OLS regression without fixed effects, OLS regression with fixed effects for country and year, and OLS regression with fixed effects for country and country-specific linear time trends. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. Unless otherwise indicated, numbers in parentheses report cluster-robust standard errors, with clustering by country. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

correlation, and endogeneity. For instance, the panel data are likely to be characterised by serial correlation because LHSL and PHN series are expected to be persistent over time. Cross-sectional dependence is also likely to be a problem because factors driving the variables in one country are likely to be present in other countries. Serial correlation and cross-sectional dependence cause inefficient estimates and biased standard errors (Chudik & Pesaran, 2013; De Hoyos & Sarafidis, 2006; Phillips & Sul, 2003; Reed & Ye, 2011; Sarafidis & Robertson, 2009; Sarafidis & Wansbeek, 2012; Sarafidis et al., 2009).

As reported in the last two rows of Tables 3.3 and 3.4 for FE with country-specific time trends, Wooldridge (2010) serial correlation test and Pesaran (2004) cross-sectional dependence test statistics are significant at the 1% significancel level. This indicates that the residuals generated from the models are serially[15] and cross-sectionally correlated using standard panel data estimators. Also, the residual series are not stationary at level.[16]

Endogeneity constitutes another issue that could arise if there are factors that are common to both economy-wide productivity and the respective dependent variables. Such common factors might be technology shocks in the health sector or unobservable risk factors associated with the health sector[17]. Lastly, non-stationarity may be an issue as Table 3.2 shows that most of the variables are not stationary at level using the heterogeneous PURT that accounts for CD. Also, the results for the residual based coinetgration technique using Pesaran's (2007) CIPS[18] test indicated that the estimated residuals are non-stationary. This

[15] The static model used in fitting the BCD data instead of estimating an autoregressive or dynamic model might be the source of serial-correlation (Durlauf & Blume, 2016, pp. 230-231; Keele & Kelly, 2005). Even though the mean grouped type estimators introduced for robustness checks can also be used to estimate dynamic models (Chudik & Pesaran, 2015) but the sample size for this study is too small to introduce extra lag variables and have sufficient degree of freedom.

[16] This indicates that the examined relationships are not cointegrated.

[17] Baltagi and Moscone (2010) adopt a similar multi-factor error structure to analyse the heterogeneous relationship between health and income for OECD countries.

[18] The appropriate critical values for CIPS procedures in testing for cointegration is not available as at the time of this research. My approach here is ad hoc and might be less robust but other earlier empirical studies (Baltagi & Moscone, 2010; Baltagi et al., 2012; Hashiguchi & Hamori, 2012) have used CIPS as a cointegration technique.

implies that there is no long-run relationship in the BCD models. But, evidence from the Pedroni (1999, 2004) coinetgration tests provided conflicting results as shown in Table 3.7. The conflicting coinetgrtaion outcomes might be due to differences in the underlying assumptions used in developing the tests. The next section checks the robustness of the preceding results by addressing these respective issues.

3.7 Robustness Checks

I address the econometric concerns identified in section 3.6 by using a set of new panel data estimators. The Panel-Corrected Standard Error (PCSE) procedure of Beck and Katz (1995) is first considered to treat serial correlation through a Prais-Winsten transformation of the variables. PCSE is a quasi-FGLS procedure that parametrically adjusts the standard errors to address cross-sectional correlation. Also, more robust panel data estimators that account for heterogeneous slope coefficients, non-stationarity, cross-sectional dependence and endogeneity in varying degree are used to investigate the robustness of the preceding results. The estimators are: Mean Group (MG) estimator by Pesaran and Smith (1995); Common Correlated Effects Mean Group (CCEMG) estimator by Pesaran (2006); and the Augmented Mean Group (AMG) Estimator by Bond and Eberhardt (2009); Eberhardt and Teal (2010).[19]

Using the alternative estimation procedures, the results for the effect of productivity on LHSL and PHN are reported in Tables 3.5 and 3.6, respectively. The productivity estimates from PCSE estimation are negative and insignificant. In most cases, estimates from the heterogeneous slopes estimators (MG and CCEMG) indicate a positive and insignificant effect of PROD on health share of labour force and relative health care prices. The AMG estimates of the effects of productivity on LSHL and PHN are negative and positive, respectively. However, in both cases, the effects are again insignificant, with none of the p-values close to the 10% significance level.

[19] The comparative characteristics of all the estimators are shown in Table A2.1 in the Appendix to Chapter 2.

The lower parts of Tables 3.5 and 3.6 generally confirm cross-sectional independence, especially for the CCEMG and AMG estimators. Also, the corresponding absolute cross-sectional correlation coefficients are very small and less than 0.37. This indicates that using the robust panel estimators addressing various econometric issues does not change the main conclusion from above: I find no support for the BCD hypotheses that productivity is related to either the share of labour in the health sector, or the ratio of prices in the health and non-health sectors.

Table 3.5: Robustness Analysis of the BCD Hypothesis: Health Sector Share of the Labour Force (*LHSL*)

Variable	PCSE	MG			CCEMG			AMG		
	(7)	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
PROD	-0.0133 (-0.16)	0.4194 (1.02)	0.0529 (0.30)	0.0433 (0.21)	2.230 (1.08)	-0.3052 (-0.57)	0.9498 (1.30)	-0.1185 (-0.47)	-0.0263 (-0.18)	-0.1789 (-0.95)
Age < 15	0.0042 (0.37)	-0.1378* (-1.91)	0.0749 (1.27)	0.0093 (0.17)	0.1987 (0.49)	0.1636 (1.12)	0.1594 (1.41)	0.0030 (0.04)	0.1168 (1.57)	0.0953 (1.34)
Age > 64	-0.0102 (-1.10)	-0.2927* (-1.75)	-0.1501 (-0.93)	0.0826 (1.40)	0.6732 (0.64)	-0.2121 (-1.34)	0.1149 (1.04)	0.3262 (1.28)	0.1820** (2.13)	0.2379*** (2.69)
Male	-0.1137** (-2.00)	0.2900 (1.07)	0.3940 (1.59)	0.4489 (1.41)	1.6617 (0.73)	0.0567 (0.43)	0.3014 (1.10)	0.0227 (0.06)	0.4734 (1.78)	0.5332* (1.76)
Life expectancy	-1.6495 (-1.45)	-2.5043 (-0.92)	1.4435 (0.52)	1.7288 (0.64)	80.477 (1.27)	0.1813 (1.00)	0.000 (0.00)	-0.6225 (-0.25)	4.7999 (0.94)	4.2263 (0.80)
Infant mortality	0.0102 (0.31)	-0.0192 (-0.30)	-0.0024 (-0.33)	0.0501 (0.65)	2.3073 (1.22)	0.2680*** (2.88)	0.2147 (1.39)	0.0404 (0.83)	0.0407 (0.63)	0.0865 (1.39)
Tobacco consumption	----	----	-0.1064 (-0.61)	-0.0687 (-0.43)	----	-0.3907 (-1.16)	-0.01725 (-0.64)	----	0.0475 (0.67)	-0.0906 (-0.65)
Alcohol consumption	----	----	0.0924 (0.43)	-0.1722 (-1.01)	----	0.1338 (0.34)	0.2757 (1.21)	----	0.0329 (0.18)	0.0003 (0.00)
GDP growth rate	----	----	----	0.0040*** (2.73)	----	----	0.0007 (0.14)	----	----	0.0046** (2.30)
Obs.	384	384	231	207	384	231	207	384	209	195
N	27	27	16	14	27	16	14	27	14	13

Variable	PCSE	MG			CCEMG			AMG		
	(7)	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
RMSE	0.0452	0.0214	0.0157	0.0154	0.0061	0.000	0.000	0.0149	0.0112	0.0099
$\lvert\hat{\bar{\rho}}\rvert$	----	*0.269*	*0.235*	*0.253*	*0.306*	*0.363*	*0.278*	*0.287*	*0.217*	*0.249*
CD_{PES}	----	*3.59****	*-0.27*	*2.43*	*-0.51*	*1.39*	*-0.73*	*1.09*	*-0.27*	*-1.18*
CIPS PURT (Error term)	----	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)	I(0)	I(0)	I(0)

NOTE: The dependent variable is *LHSL*. MG, CCEMG and AMG models are estimated with country specific linear time trends. Pesaran (2004) cross-sectional dependence (CD) procedure is used as a post-estimation test. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. RMSE is root mean square error. $\lvert\hat{\bar{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) CD test. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.6: Robustness Analysis of the BCD Hypothesis: Ratio of Prices in the Health and Non-Health Sectors (*PHN*)

Variable	PCSE	MG			CCEMG			AMG		
	(7)	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
PROD	-0.0109 (-0.04)	-0.4608 (-1.05)	0.3823 (0.43)	1.2333 (0.87)	-1.2845 (-1.15)	1.6711 (0.38)	-1.7717 (-1.23)	0.0706 (0.17)	0.7511 (0.98)	1.5263 (1.18)
Age < 15	-2.8143** (-2.01)	4.6137 (0.99)	-2.0201 (-0.22)	-7.5154 (-0.77)	-4.9472 (-0.34)	21.049 (1.39)	-12.977 (-1.12)	4.5238 (0.68)	-8.4848 (-0.67)	-16.022 (-1.28)
Age > 64	2.0472 (0.94)	-0.2015 (-0.05)	-1.2941 (-0.16)	-12.306 (-0.86)	-16.976 (-0.86)	2.0265 (0.08)	-11.809* (-1.66)	-5.8912 (-0.98)	-4.8905 (-0.57)	-12.027 (-0.71)
Male	-1.1243 (-0.31)	-12.109 (-0.78)	-57.712* (-1.91)	6.7222 (0.20)	-29.474 (-0.76)	-32.313 (-0.80)	-4.7541 (-1.45)	-18.611 (-1.00)	-22.205 (-0.69)	35.769 (0.93)
Life expectancy	0.38500 (0.30)	1.8635 (1.47)	-2.6853 (-0.92)	0.2631 (0.07)	3.5077 (1.17)	6.7257 (0.63)	10.596** (2.29)	2.8260** (1.99)	2.3560 (0.90)	5.0426* (1.72)
Infant mortality	-0.0312 (-0.06)	-0.5051 (-0.43)	-1.8834 (-0.92)	0.1729 (0.10)	2.5771 (1.37)	3.5500 (0.51)	3.1567 (1.03)	1.467** (2.18)	2.1219 (1.23)	3.2519* (1.78)
Tobacco consumption	----	----	-0.0103 (-0.81)	-0.0165 (-1.49)	----	-0.0071 (-0.42)	0.0054 (0.56)	----	0.0014 (0.31)	-0.0028 (-0.45)
Alcohol consumption	----	----	4.2884* (1.86)	3.1031 (1.27)	----	4.4609 (0.48)	0.0174 (0.00)	----	6.0544** (2.09)	4.4153 (1.48)
GDP growth rate	----	----	----	0.4297 (1.33)	----	----	-1.0515 (-1.56)	----	----	-0.2203 (-0.61)
Obs.	382	382	203	201	382	203	201	382	203	201
N	21	21	12	12	21	12	12	21	12	12

Variable	PCSE	MG			CCEMG			AMG		
	(7)	(7)	(8)	(9)	(7)	(8)	(9)	(7)	(8)	(9)
RMSE	4.4700	2.8747	2.2838	2.0046	1.1665	0.000	0.000	2.2307	1.3124	1.1452
$\lvert\bar{\hat{\rho}}\rvert$	----	*0.277*	*0.282*	*0.267*	*0.320*	*0.317*	*0.322*	*0.261*	*0.317*	*0.253*
CD_{PES}	----	*2.95****	*0.81*	*2.25***	*-1.22*	*2.50***	*0.20*	*-2.30***	*-1.99***	*-0.66*
CIPS PURT (Error term)	----	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(0)	I(0)	I(0)

NOTE: The dependent variable is *LHSL*. MG, CCEMG and AMG models are estimated with country specific linear time trends. Pesaran (2004) cross-sectional dependence (CD) procedure is used as a post-estimation test. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. RMSE is root mean square error. $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) CD test. Cross-sectionally augmented Im et al. (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3.7: Pedroni's (2004) Cointegration Results

Statistic	*Pedroni's (2004) Cointegration Tests*		
	Ln(LHSL)		*PHN*
Panel: v	-4.161***		-2.61***
Panel: rho	5.128***		3.715***
Panel: t	-7.722***		-5.482***
Panel: ADF	1.647**		3.651***
Group: rho	7.501***		5.744***
Group: t	-10.17***		-7.995***
Group: ADF	1.765**		1.528*
N	27		21
T (average per unit)	14		18
Number of Regressors	6		6
Standardised Critical Values (one-tail):	1%	5%	10%
	2.326	1.645	1.282
Null Hypothesis: "No Cointegration"	Reject		Reject

NOTE: Dependent variables: LHL (Health Sector Share of the Labour Force); and PHN (Ratio of Prices in the Health and Non-Health Sectors); and OPE (Real out-of-pocket health expenditure per capita). All the regressors in Model (1) as listed on Table 3.3-3.6 are used for this test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

3.8 Conclusion

This chapter makes a number of contributions to the literature on Baumol's Cost Disease theory. I have developed a theoretical model of BCD that provides an explicit link between the theory underlying BCD and estimated models. In particular, I have derived two testable hypotheses that directly capture the predictions and main characteristics of the BCD framework. I then test these hypotheses on a sample of 27 OECD countries over the period 1995-2013, using a wide variety of model specifications and panel data estimators. One key feature of this theoretical model set-up for testing BCD hypotheses is that it utilises a precise measure of the non-health price index, as opposed to the GDP deflator employed in other studies.

The empirical hypotheses developed in this chapter predict a relationship between the economy's productivity (proxied by GDP per number of hours worked) and (i) the share of the economy's labour force employed in the health sector, and (ii) the ratio of prices in the health and non-health sectors. BCD implies positive correlations for both sets of relationships. In a range of model specifications and estimation procedures, I do not find a significant relationship to support the BCD predictions for OECD countries. This may be due to the failure of the BCD model for "non-progressive" sectors like health care to account for technology improvements and the resulting substitutability of capital for labour inputs. Recently, the health care industry has experienced innovative growth in medical devices, software, and healthcare administration, such as robotic surgery, robotic nurse assistant, and remote patient monitoring systems. These innovations are likely to lead to further departures from the original BCD framework. As a result, it may no longer be appropriate to think of the health sector as technologically "non-progressive" -- if it ever was. In any case, the findings of this study indicate that health care does not seem to be "trapped" in a dismal world of stagnant productivity and inexorably rising costs from labour employment.

Chapter 4: Accounting for Heterogeneous and Non-stationary Multifactor Error Structure in Panel Dataset: New Monte Carlo Simulation Experiments

Chapter Four

4.1 Introduction

In the last three decades, there have been significant developments and advancements in the understanding of how to estimate economic relationships from time series, cross-sectional and panel data. The availability of open-source datasets characterized by large N (groups of cross-sectional units) and T (number of time periods) from major repositories such as the OECD[20], World Bank, IMF[21], WHO[22], and Penn-World Table have spurred this development. Pesaran, Shin, and Smith (1999, pp. 621-622) call datasets with N = 24 and T = 32 as "quite large", and N = 10 and T = 17 as "quite small". Pedroni (2008) classifies "macro panels" as having N less than 100 and T greater than 20; with "micro panels" consisting of T less than 5 or 10 and N very large, having hundreds or even thousands of cross-sectional units. The different types of datasets have motivated the development for customized estimators that are most appropriate for a given research application.

The use of macro panels in modelling raises a number of challenges, while opening up new possibilities. With large macro panels, pooling data to estimate long-run coefficients may not be necessary. As noted by Pesaran and Smith (1995, p. 80)[23] "when T is large enough it is sensible to run separate regressions for each group" to estimate the average effects. This is advantageous because it allows one to avoid the widely adopted assumption of slope homogeneity across cross-sectional units, such as countries. Second, most of the macro panels used by applied econometricians are believed to be characterized by non-stationarity (with suspected slope heterogeneity) that violate the assumptions of conventional panel data

[20] Organisation for Economic Co-operation and Development (*OECD*)
[21] International Monetary Fund (IMF)
[22] World Health Organisation (WHO)
[23] Pesaran and Smith (1995) provide extensive description and implications of the procedures to estimate the average effect across groups when T is large. Among the procedures is the mean group estimator that estimates the average coefficient explicitly and is found to be more consistent for static and dynamic panel models.

estimators. Lastly, thinking about economic relationships in macro panels has developed to where modellers now frequently presume that unobserved, common factors underlie many of the observed relationships among economic variables.

With respect to the latter, recent applied and theoretical panel data econometric studies have emphasized the existence of cross-sectional or "between groups" dependence among the disturbances (i.e. $cor(e_{it}, e_{jt}) \neq 0$). This has been attributed to unobserved "common shocks" and unobserved time-variant heterogeneous error components (Anselin, 2001; Baltagi, 2005; De Hoyos & Sarafidis, 2006; Eberhardt & Teal, 2011, 2014; Pesaran, 2004, 2006; Pesaran & Tosetti, 2011; Phillips & Sul, 2003; Robertson & Symons, 2000; Sarafidis & Wansbeek, 2012).

Although the existence of cross-sectional dependence has been recognized since the 1930s as noted in the works of Stephan (1934), Neprash (1934), and Fisher (1935), but it has often been ignored by researchers in panel model estimation. Cross-sectional dependence can have severe implications for the efficiency and consistency properties of standard panel estimators such as pooled ordinary least squares (POLS), fixed effects (FE) and random effects (RE). The impact of cross-sectional dependence in estimation varies (Coakley et al., 2006) but is dependent on two major factors: (i) the size of the average pairwise cross-sectional correlation; and (ii) the nature or source of the cross-sectional correlation (De Hoyos & Sarafidis, 2006).

For instance, in a case where the cross correlation of errors emanates from the omission of common effects or unobserved spatial effects, but where the errors are uncorrelated with the explanatory variables (i.e. $cor(e_i, X) = 0$), the conventional panel estimators (POLS, RE, and FE) can result in inefficient estimates and biased standard errors (Chudik & Pesaran, 2013; De Hoyos & Sarafidis, 2006; Phillips & Sul, 2003; Reed & Ye, 2011; Sarafidis & Robertson, 2009; Sarafidis & Wansbeek, 2012; Sarafidis et al., 2009). Where the unobserved common factors induce correlation between the disturbance and regressors (i.e. $cor(e_i, X) \neq 0$), it creates an endogeneity problem.

In recognition of the implications of slope heterogeneity, cross-sectional dependence, non-stationarity, and endogeneity induced by the presence of unobserved common factors, new panel data estimators have been developed to accommodate one or more of these econometric issues. Among these recent estimators[24] are Pesaran and Smith (1995) Mean Group (MG) estimator, Pesaran (2006) Common Correlated Effects Mean Group (CCEMG) estimator, and the Augmented Mean Group (AMG) estimator by Bond and Eberhardt (2009) and Eberhardt and Teal (2010).

This chapter is concerned with investigating the performances of these mean group type estimators relative to the pooled type methods under different panel model set-ups. It will do so through the use of Monte Carlo simulation experiments. Bond and Eberhardt (2013a, henceforth B&E) perform similar experiments by extending the Data Generating Processes (DGP) of Coakley et al. (2006), and Kapetanios, Pesaran, and Yamagata (2011). This study first replicates the simulation experiments in B&E (2013) using the same Monte Carlo DGP (i.e. simulated dataset) set-ups. It then extends the analysis to incorporate additional performance metrics for comparing the respective estimators.

The last experiment specifically replicates the first simulation for three sets of panel data dimensions (N = 28 and T = 21; N = 23 and T = 21; and N = 51 and T = 21). These are chosen to match typical panel data dimensions available in World Development Indicators

[24] A brief description and comparison between the standard (i.e. pooled type) estimator and the recent (i.e. mean group type) estimators are shown at appendix 4.5 (TABLE A4.1). The assumptions and properties of the estimators are extensively discussed in the literature (see Banerjee et al., 2010; Beck & Katz, 2007; Bond & Eberhardt, 2009; Chudik & Pesaran, 2013; Eberhardt & Teal, 2010, 2011, 2014; Pesaran, 2006; Pesaran & Smith, 1995; Poi, 2003; Swamy, 1970).

(WDI) in order to provide guidance for my subsequent analysis in chapter five of the income elasticity of health spending for selected African countries.

4.2 Panel Data Model and Estimation Procedure

This chapter considers the following general empirical cross-section time series model set-up[25] for $i = 1,..., N$ (number of cross-section groups), $t = 1,..., T$ (time periods), $k = 1,..., K$ (explanatory variables), and $m = 1,..., M$ (number of factors):

$$y_{it} = \alpha_i' d_t + \beta_{k,i}' x_{k,it} + u_{it} \tag{4.1}$$

$$u_{it} = \lambda_{i,m}' f_{t,m} + \varepsilon_{it} \tag{4.2}$$

$$x_{k,it} = \pi_{k,i}' d_t + \delta_{k,m,i}' g_{m,t} + p_{k,m,i} f_{m,t} + v_{k,it} \tag{4.3}$$

The slope of k observed explanatory variables in Eq. (4.1) is heterogeneous and follows a random coefficient process with common slope vector (β):

$$\beta_i = \beta + \eta_i \tag{4.4}$$

The factor loadings that represent the effect of the unobserved common factors, f_t and g_t , (cf. Eq. (4.2) and Eq. (4.3)) are heterogeneous of the form:

$$\lambda_i = \lambda + \zeta_i \tag{4.5}$$

$$\delta_i = \delta + \zeta_i \tag{4.6}$$

$$p_i = p + \zeta_i \tag{4.7}$$

[25] The matrix algebra with corresponding dimensions of the model set-up is presented in Appendix 4.2.

The m factors are time-variant but cross-sectionally invariant and they are specified to model cross-sectional dependence. The errors (η_i and ζ_i) are independent and identically distributed across groups, i. Similarly, the idiosyncratic terms (ε_{it} and v_{it}) in Eq. (4.2) and Eq. (4.3) have fixed mean and finite variance. The model set-up also incorporates a vector of observed common effects (d_t) in the form of seasonal dummies or deterministic country-specific effects (cf. Eq. (4.1) and (4.3)). The effects are differential for each individual group (α_i and $\pi_{k,i}$). To further enrich the set-up, the observables (y_{it}, x_{it}) and unobservables (f_t, $g_{m,t}$) have the potential to be non-stationary ($|\vartheta| \leq 1$ and $|\kappa| \leq 1$):

$$f_t = \vartheta' f_{t-1} + \omega_t \tag{4.8}$$

$$g_t = \kappa' g_{t-1} + \omega_t \tag{4.9}$$

Another key aspect of the model is the unobserved common factors overlap in Eq. (4.2) and Eq. (4.3). This creates an identification problem for the estimation of the heterogeneous slopes, β_i.[26]

The model set-up above can be used to express different types of panel data models by the imposition of appropriate restrictions. Examples include Pooled Ordinary Least Squares ($\alpha_i = \alpha$, $d_t = 1$, $\beta_i = \beta$, $\{\lambda_i, \delta_i, p_i\} = 0$), the Fixed and Random Effects models ($d_t = 1$, $\beta_i = \beta$, $\{\lambda_i, \delta_i, p_i\} = 0$), Two-way Fixed Effects (2WFE) ($\beta_i = \beta$, $\{\lambda_i, \delta_i, p_i\} = 0$), the Swamy (1970) Random Coefficients Model (RCM) ($d_t = 1$, $\{\lambda_i, \delta_i, p_i\} = 0$) and the Pesaran & Smith (1995) Mean Group (MG) model ($\{\lambda_i, \delta_i, p_i\} = 0$). The pooled type estimators (POLS,

[26] Substituting (4.3) and (4.2) into (4.1):
$$y_{it} = \left(\alpha_i' + \pi_{k,i}' \beta_i'\right) d_t + \left(\delta_{k,m,i}' \beta_i'\right) g_{m,t} + \left(\lambda_i' + p_{k,m,i} \beta_i'\right) f_{m+1,t} + \beta_i' v_{k,it} + \varepsilon_{it}$$

FE, RE, and 2WFE) assume stationarity of the observable variables, cross-sectional independence among disturbances, and slope homogeneity. The RCM model differs from the MG estimator in that the latter is based on the simple average of group-specific OLS estimates (see Hsiao & Pesaran, 2004 for extensive comparison between the models). Coakley et al. (2006), similarly provide detailed comparison between the pooled and mean group type models.

Pesaran (2006) developed the CCEMG estimator to estimate N, group-specific regressions by augmenting the model set-up (cf. Eq. (4.1)) with cross-sectional averages of the dependent variable and regressors. For each cross-section unit, the following model is estimated:

$$y_{it} = \alpha_i' d_t + \beta_{k,i}' x_{k,it} + \theta_{1i}' \bar{y}_t + \theta_{2k,i}' \bar{x}_{k,t} + u_{it} \tag{4.10}$$ [27]

The augmented covariates $\bar{y}_t$ (T x 1) and $\bar{x}_{k,t}$ (T x *k*) are proxies for the unobserved common factors, f_t, causing correlation among error disturbances and between error disturbances and regressors. A simple or weighted average of the estimated slope coefficients across group is computed to derive the average effect:

$$\hat{\beta}_{CMG} = N^{-1} \sum_i \hat{\beta}_i \tag{4.11}$$

From Eq. (4.10), the Pesaran (2006) Pooled Common Correlated Effect (CCEP) estimator model can be derived with a few restrictions ($\beta_i = \beta$) as:

[27] See appendix 4.3 for the derivation of the cross-sectional averages for proxing the common factors.

$$y_{it} = \alpha_i' d_t + \beta_k' x_{k,it} + \theta_{q,1}' \bar{y}_t^* + \theta_{q,2,k}' \bar{x}_{k,t}^* + u_{it} \qquad (4.12)^{28}$$

where $q = 1,..., N$; $\bar{y}_t^* = \mathrm{I} \otimes \bar{y}_t$; $\bar{x}_t^* = \mathrm{I} \otimes \bar{x}_t$; I is $(N \times N)$; $\bar{y}_t$ and $\bar{x}_t$ are $(T \times 1)$ cross-section averages over time; and the Kronecker product gives an $(NT \times N)$ matrix. The β in Eq. (4.12) is estimated using pooled OLS.

In the same spirit, Bond and Eberhardt (2009) and Eberhardt and Teal (2010) developed the Augmented Mean Group (AMG) estimator to estimate the average effect using a different approach to account for the unobserved common shocks. The AMG implementation is based on a three step procedure (Bond & Eberhardt, 2013a). The first step involves estimating the "common dynamic process" ($\hat{c}_t \equiv \hat{\mu}_t^\bullet$) from the estimated first difference pooled OLS (FD-OLS) model augmented with T- 1 year dummies, ΔD_t

$$\Delta y_{it} = \alpha_i + \beta' \Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + u_{it} \qquad (4.13)$$

The extracted estimated slope of ΔD_t ($\hat{c}_t$) is designed to explicitly capture the unobserved common factor. The common dynamic process can either be subtracted from the dependent variable (cf. Eq. (4.14), denoted subsequently as AMG(i)) or incorporated as an additional covariate (cf. Eq. (4.15), denoted subsequently as AMG(ii)):

$$y_{it} - \hat{\mu}_t^\bullet = \alpha_i + \beta_i' x_{it} + \tau_i t + u_{it} \qquad (4.14)$$

$$y_{it} = \alpha_i + \beta_i' x_{it} + d_i \hat{\mu}_t^\bullet + u_{it} \qquad (4.15)$$

[28] The number of parameters to be estimated for the CCEP estimator if $d_t = 1$, and $k = 1$ is $(N \times 3) + k$ with the degrees of freedom of $NT - (N \times 3) - k$.

N, group-specific regressions of either Equation (4.14) or (4.15) are estimated and the average of the coefficients are taken as shown in Equation (4.11).

The major difference between the CCEMG and the AMG is the approach of accounting for the unobserved common factors. Both estimators maintain the same underlying assumptions (Bond & Eberhardt, 2013a) for estimating a static panel model when the regressors are strictly exogenous as noted in Chudik and Pesaran (2015)[29]. B&E also consider two other "infeasible" estimators: a FE(inf) and a MG(inf) that append the FE and MG estimators with the unobserved common factors as additional regressors. These are included for comparison purposes only since the unobserved common factors are, by definition, unobserved, thus rendering these estimators "infeasible."

4.3 Simulation I: Replication and Extension of Bond and Eberhardt (2013a)

This section of the study presents the data generating process (DGP) and Monte Carlo simulation set-ups for comparing the performances and checking robustness of the estimators of interest in the presence of the previously described econometric issues. The highlighted issues include error cross-sectional dependence, slope heterogeneity, non-stationarity of the observable and unobservable series, and endogeneity. The experiment involves 1000 simulations with $N = 50$, $T = 30$ and $T + T_0$[30] dimension sets, where $T_0 = 1,...,50$. The first 50 observations for each cross-section units were ignored (burned off) for estimation purposes. The N and T sizes considered for the simulation are typical of macroeconomic panel datasets in monthly, quarterly or annual frequency.

4.3.1 Data Generating Process (DGP) Set-Up

[29] Chudik and Pesaran (2015) extend the CCEMG method to accommodate dynamic panel models when the regressors are strictly and/or weakly exogenous.

[30] The 50 observations are imposed and added to each dimension of T to have a balanced dataset after differencing each series. Other previous simulation experiments (Bond & Eberhardt, 2013a; Coakley et al., 2006; Kapetanios et al., 2011) adopted similar approach.

The DGP for $i = 1,..., N$; $t = 1,..., T$; $K = 1$; and $m = 1,2,3$ follows:

$$y_{it} = \beta'_{k,i} x_{k,it} + u_{it} \qquad u_{it} = \alpha_i + \lambda'_{1,i} f_{1,t} + \lambda'_{2,i} f_{2,t} + \varepsilon_{it} \qquad \varepsilon_{it} = \psi_i \varepsilon_{i,t-1} + \tau_{it} \tag{4.16}$$

$$x_{it} = \pi_i + \delta'_{1,i} f_{2,t} + \delta'_{2,i} f_{3,t} + v_{it} \qquad v_{it} = \rho_i v_{i,t-1} + e_{it} \tag{4.17}$$

$$f_{m,t} = \phi_m + \vartheta'_m f_{m,t-1} + \omega_{m,t} \qquad \omega_{m,t} = \gamma_m \omega_{m,t-1} + \upsilon_{m,t} \tag{4.18}$$

I use the same parameter settings as Bond and Eberhardt (2013a) for replicating the baseline simulation and subsequent extensions. The intercepts in the y, x and f models are generated as:

$\alpha_i \sim iid \quad U[1.5, \quad 2.5]$ where $\alpha \equiv E(\alpha_i) = 2$

$\pi_i \sim iid \quad U[4, \quad 6]$ where $\pi \equiv E(\pi_i) = 5$

$\phi_m = \{0.015, \quad 0.012, \quad 0.01\}$ for $m = 1,2,3$

The stationarity and autocorrelation specifications for the error disturbances in the y, x and f equations as well as the lag of the unobservable common factors coefficients are generated as follows:

Error disturbance in y***:*** $\psi_i = 0$ (Stationary, I(0); No autocorrelation; Cointegration; No simultaneity/ feedback effects)

Error disturbance in x***:*** $\rho_i \equiv \rho = 0.25$ (Homogeneous serial correlation across groups)

Error disturbance in f_m : $\gamma_m = 0$ (No autocorrelation)

Lag of unobservable common factors ($f_{m,t-1}$***) coefficients:*** $\vartheta_m = 1$ (Non-stationary factors, I(I))

The set-up for the error terms in the data generation process are derived as:

$\tau_{it} \sim iid \quad N(0, \sigma_\tau^2)$ where $\sigma_\tau^2 = 0.00125$

$e_{it} \sim iid \quad N(0, \sigma_{e,i}^2)$ where $\sigma_{e,i}^2 \sim U[0.001, \quad 0.003]$

$\upsilon_{m,t} \sim iid \quad N(0, \sigma_{\upsilon,m}^2)$ where $\sigma_{\upsilon,m}^2 = 0.00125$

The heterogeneous parameters in the y and x models are defined as:

Regressor:

$\beta_i = \beta + \eta_i$ where $\beta = 1$; $\eta_i \sim U[-0.25, \quad 0.25]$; and $\beta_i \sim U[0.75, \quad 1.25]$

Factor Loading: y equation

for $\lambda_{1,i} = \lambda_1 + \zeta_{1,i}$; where $\lambda_1 = 0.5$; $\zeta_i \sim U[-0.5, \quad 0.5]$, then $\lambda_{1,i} \sim U[0, \quad 1]$;

for $\lambda_{2,i} = \lambda_2 + \zeta_{2,i}$; where $\lambda_2 = 0.75$; $\zeta_i \sim U[-0.5, \quad 0.5]$, then $\lambda_{2,i} \sim U[0.25, \quad 1.25]$

***Factor Loading*: x** equation

for $\delta_{1,i} = \delta_1 + \zeta_{1,i}$; where $\delta_1 = 0.5$; $\zeta_i \sim U[-0.5, \quad 0.5]$, then $\delta_{1,i} \sim U[0, \quad 1]$;

for $\delta_{2,i} = \delta_2 + \zeta_{2,i}$; where $\delta_2 = 0.75$; $\zeta_i \sim U[-0.5, \quad 0.5]$, then $\delta_{2,i} \sim U[0.25, \quad 1.25]$

The serial correlation corrected data generating process for the x equation in (4.18) is derived as:

$$
\begin{aligned}
x_{it} &= \pi_i + \delta'_{1,i} f_{2,t} + \delta'_{2,i} f_{3,t} + \rho_i \left(x_{i,t-1} - \left(\pi_i + \delta'_{1,i} f_{2,t-1} + \delta'_{2,i} f_{3,t-1} \right) \right) + e_{it} \\
&= (1 - \rho_i)\pi_i + \rho_i x_{i,t-1} + \delta'_{1,i} f_{2,t} - \rho_i \delta'_{1,i} f_{2,t-1} + \delta'_{2,i} f_{3,t} - \rho_i \delta'_{2,i} f_{3,t} + e_{it}
\end{aligned}
\tag{4.19}
$$

The DGP for the y equation in (4.16) can also be generated as:

$$
\begin{aligned}
y_{it} &= \alpha_i + \beta'_{k,i} x_{k,it} + \lambda'_{1,i} f_{1,t} + \lambda'_{2,i} f_{2,t} + \psi_i y_{it-1} - \psi_i \begin{pmatrix} \alpha_i + \beta'_{k,i} x_{k,i,t-1} + \\ \lambda'_{1,i} f_{1,t-1} + \lambda'_{2,i} f_{2,t-1} \end{pmatrix} + \tau_{it} \\
&= (1 - \psi_i)\alpha_i + \psi_i y_{it-1} + \beta'_{k,i} x_{k,it} - \psi_i \beta'_{k,i} x_{k,it} + \lambda'_{1,i} f_{1,t} - \psi_i \lambda'_{1,i} f_{1,t-1} \\
&\quad + \lambda'_{2,i} f_{2,t} - \psi_i \lambda'_{2,i} f_{2,t-1} + \tau_{it}
\end{aligned}
\tag{4.20}
$$

The DGPs of x_{it} and y_{it} in equation (4.19) and (4.20) are generated to correct for serial correlation induced by the first order autoregressive (AR(1)) process of errors (v_{it}) in x_{it} (see equation (4.17)). The AR(1) error is further transmitted to y_{it} through x_{it}.

Case I: Baseline Model

The key features of the baseline model as described above are nonstationarity in the unobserved common factors, $f_{m,t}$, and heterogeneity in the slope coefficients, β_i. The first experiment consists of replicating Bond and Eberhardt (2013a) baseline Monte Carlo simulation with N =50 and T = 30. My subsequent experiments follow Bond and Eberhardt (2013a) in extending their baseline set-up by incorporating heterogeneous linear trends; a feedback effect where shocks to *y* affect *x* with a one-period lag; and the individual cross-sectional units *i* are divided into two groups ("clubs") with each group characterized by a common slope coefficient, β_i. These extensions are described in more detail below:

Case II: Heterogeneous Linear Trends ($\varpi_i t$)

Case I is augmented with heterogeneous linear time trends $(\varpi_i t)$ for the DGP for y (cf. Eq. (4.16)) as follows:

$$y_{it} = \beta'_{k,i} x_{k,it} + u_{it} \qquad u_{it} = \alpha_i + \lambda'_{1,i} f_{1,t} + \lambda'_{2,i} f_{2,t} + \varpi_i t + \varepsilon_{it} \tag{4.21}$$

$$y_{it} = \beta'_{k,i} x_{k,it} + \alpha_i + \lambda'_{1,i} f_{1,t} + \lambda'_{2,i} f_{2,t} + \varpi_i t + \varepsilon_{it} \tag{4.22}$$

$\varpi_i = \varpi + o_i$ where $\varpi = 0.005$; $o_i \sim U[-0.025, \quad 0.025]$; and $\varpi_i \sim U[-0.02, \quad 0.03]$

Case III: Feedback Effect

From Case I, $\psi_i \neq 0$, $\psi_i = 0.25$, and $\varepsilon_{i,t-1}$ (where $\varepsilon_{it} \sim iid \quad N(0, \sigma_\varepsilon^2)$, and $\sigma_\varepsilon^2 = 0.00125$) is included in the x equation to create feedback effects. Bond and Eberhardt (2013a) describe the feedback effect as an idiosyncratic shock from y to x, with a one period lag. The disturbance term in y is non-stationary (I(1)) and not cointegrated. Incorporating these changes into the DGP for y yields

$$y_{it} = \beta'_{k,i}\left(x_{k,it} + \psi_i \varepsilon_{i,t-1}\right) + \alpha_i + \lambda'_{1,i} f_{1,t} + \lambda'_{2,i} f_{2,t} + \tau_{it} \tag{4.23}$$

For $k = 1$, x_{it} is re-generated as defined in Eq. (4.24). Accordingly, the DGP for x is:

$$\begin{aligned} x_{it} &= \pi_i + \delta'_{1,i} f_{2,t} + \delta'_{2,i} f_{3,t} + \psi_i \varepsilon_{i,t-1} + \rho_i \left(x_{i,t-1} - \begin{pmatrix} \pi_i + \delta'_{1,i} f_{2,t-1} + \\ \delta'_{2,i} f_{3,t-1} \end{pmatrix} \right) + e_{it} \\ &= (1-\rho_i)\pi_i + \rho_i x_{i,t-1} + \delta'_{1,i} f_{2,t} - \rho_i \delta'_{1,i} f_{2,t-1} + \delta'_{2,i} f_{3,t} - \rho_i \delta'_{2,i} f_{3,t} + \psi_i \varepsilon_{i,t-1} + e_{it} \end{aligned} \tag{4.24}$$

Case IV: Beta Clubs

In this case, the restriction that the regressor slope coefficient consists of a common component, β, across all cross-sectional units is relaxed to allow two different common components, β_1 and β_2. This is done to capture the notion of "clubs." 80% of the cross-sectional units have $\beta = 0.75$. 20% have $\beta = 2$. These values are chosen so that across all cross-sectional units, the common vector of the regressor slope coefficient has an average of one. Each cross-sectional unit's slope coefficient continues to also have a random component.

4.3.2 Measures of Estimator Performance

For performance measures, B&E use the mean, median, standard deviation, and mean of the standard errors of the estimated slope coefficients for x, $\hat{\beta}_i$. This study extends B&E's analysis by also including measures of efficiency and coverage rates. Both measures are calculated over the estimates produced from 1000 simulations. Efficiency is defined by root mean square error for the estimated slope coefficient, $\hat{\beta}_i$:

$$RMSE = \sqrt{\frac{\sum_{r=1}^{1000}\left(\hat{\beta}_{i,(ESTIMATOR)}^{(r)} - \beta_i\right)^2}{1000}} \tag{4.25}$$

The coverage rate is defined as the percentage of 95% confidence intervals around $\hat{\beta}_i$ that include the true value, β_i. If the coverage rate is less than 95%, it means the null-hypothesis $\left(\hat{\beta}_i^{(r)} = \beta_i\right)$ is over-rejected.

I use a colour code system to identify "relatively good," "relatively neutral," and "relatively bad" performance. The thresholds for each category were determined through a combination of natural sorting of the data and objective standards. For example, for RMSE, the respective values were observed to group themselves into three categories: (i) RMSE < 0.0050, (ii) 0.0050 ≤ RMSE ≤ 0.0100, and (iii) RMSE > 0.0100. Accordingly, these three categories were classified as "relatively good," "relatively neutral," and "relatively bad," respectively. Alternatively, coverage rates between 0.90 and 0.99 were classified as "relatively good" as these were reasonably close to the target, 95% confidence level. Coverage rates less than 0.85 and equal to 1.00 were considered "relatively bad" because these values implied that hypothesis tests would be substantially impaired. Values within these two ranges were classified as "relatively neutral." The respective classification criteria are given in Table 4.1 below.

Table 4.1: Performance Criteria

	RMSE	***COVERAGE RATE (= CVR)***
Relatively Good (Green)	RMSE < 0.0050	0.90 ≤ CVR ≤ 0.99
Relatively Neutral (White)	0.0050 ≤ RMSE ≤ 0.0100	(i) 0.85 ≤ CVR < 0.90 (ii) 0.99 < CVR < 1.00
Relatively Bad (Red)	RMSE > 0.0100	(i) CVR < 0.85 (ii) CVR = 1.00

4.3.3 Monte Carlo Results

Replication of B&E's simulation experiments for the four different DGP set-ups was carried out using two versions of GAUSS, Versions 9 and 16. Version 9 was the version used by B&E. Version 16 was the most recent version of GAUSS at the time this research was undertaken. The packages differ in their random number generators and produce somewhat different results. This section presents the descriptive statistics, efficiencies and coverage rates for each of the replicated experiments. The study replicated 100 experiments covering four model set-ups according to specific panel dimensions (N and T). Results for $(N = 50, T = 30)$ are presented in Tables 4.2 to 4.5. These dimensions were chosen because they are representative of many studies that appear in the literature.

For the results shown in Table 4.2-4.5, differences in the mean between the original and replicated coefficient estimates that were larger than 0.0005 are yellow-highlighted. Note that B&E did not report performance measures for efficiency and coverage rates, so no comparison with respect to these measures is possible. Results for the baseline (Table 4.2), feedback (Table 4.4), and beta-club (Table 4.5) replications were generally very close to B&E's reported results. In contrast, the results for the heterogeneous trend case (Table 4.3) are substantially different. The latter result is likely due to differences in the code used by B&E and myself. While I received B&E's code for replicating Tables 4.2, 4.4, and 4.5, I had to write my own code for Table 4.3. When I could not replicate B&E's results for this case, I contacted B&E and sent them my results and code. However, they were unable to resolve the discrepancy for me.

The results for the baseline experiments are reported in Table 4.2. To facilitate reading of the table, the respective estimators are described again in the note below the table. The first five estimators (POLS, 2WFE, CCEP, FD-OLS, and FE(inf)) are the "pooled" estimators. The next five estimators (CCEMG, AMG(i), AMG(ii), MG, and MG(inf)) are the "mean group" estimators. It must be noted again that FE(inf) and MG(inf) are included for comparison purposes only. They are "infeasible" for actual data analysis because they include the common factors as variables in the estimation, and thus presume that they are observed. In evaluating the different estimators, I considered all the three performance measures (MEAN, RMSE, and COVERAGE RATE). Good performance for MEAN consists of a value close to 1.0000. (Relatively) good performance for the RMSE and COVERAGE RATE measures is indicated by a green colour-coding.

Among the feasible pooled estimators, only the Common Correlated Effect Pooled Estimator (CCEP) does well across all three performance measures. Both B&E and my replications using the two versions of GAUSS produce a mean estimate of β close to 1.000. Efficiency is comparable to the two infeasible estimators (0.0007 versus 0.0003), as are coverage rates (91.3% and 91.6%). The First Difference Ordinary Least Squares (FD-OLS) estimator just misses out on being "relatively good" across the board because its coverage rate for the GAUSS (Version 16) experiments was just shy of 90%.

Noteworthy is the poor performance of the two pooled estimators, Pooled Ordinary Least Squares (POLS) and Two-Way Fixed Effects (2WFE). These two estimators are workhorse estimators for many empirical analyses using panel data. However, the baseline Monte Carlo environment of nonstationarity in the unobserved common factors and heterogeneity in the slope coefficient brings out poor performance. Both estimators demonstrate substantial bias, with the mean estimate approximately 3 percent off its true value. Both estimators are relatively inefficient, with the POLS estimator being particularly so. And both estimators produce coverage rates far off the mark. Substantially more than half of the respective 95% confidence intervals do not include the true value of β. This renders hypothesis testing with these two estimators virtually useless.

Among the mean group estimators, the Common Correlated Effect Mean Group estimator (CCEMG) and the two Augmented Mean Group estimators (AMG(i) and AMG(ii)) perform well – about as well as the CCEP estimator. Interestingly, the simple Mean Group estimator (MG) has bad performance that rivals the worst of the pooled estimators.

Table 4.3 extends the analysis by adding heterogeneous time trends to the DGPs generating the y's. Among the pooled estimators, the CCEP and FD-OLS estimators trade places with respect to performance. FD-OLS performs well across all performance measures, with CCEP slipping slightly with respect to coverage rates. Among the mean group estimators, the CCEMG, AMG(i) and AMG(ii) estimators generally perform well. Once again, the POLS, 2WFE, and MG estimators perform poorly across all three performance measures. All three estimators show dismal coverage rates. In addition, the MG estimator demonstrates substantial bias (approximately 13%).

Table 4.2: Performance Comparison (Case I – Baseline)

ESTIMATOR	*MEAN*			*RMSE*		*COVERAGE RATE*	
	B&E (2013)	*Replication (GAUSS)*		*Replication (GAUSS)*		*Replication (GAUSS)*	
		Version 9	*Version 16*	*Version 9*	*Version 16*	*Version 9*	*Version 16*
POLS	0.9754	0.9754	0.9758	0.0457	0.0443	29.1	29.7
2WFE	1.0324	1.0324	1.0321	0.0083	0.0083	45.8	45.7
CCEP	0.9995	0.9995	1.0004	0.0007	0.0007	91.3	91.6
FD-OLS	1.0021	1.0021	1.0016	0.0007	0.0008	91.3	89.7
FE(inf)	1.0000	1.0000	1.0006	0.0003	0.0003	92	91.5
CCEMG	0.9992	0.9992	0.9994	0.0007	0.0007	98.9	97.8
AMG(i)	1.0026	1.0026	1.0026	0.0006	0.0007	98.4	97.8
AMG(ii)	1.0018	1.0018	1.0018	0.0006	0.0006	97.7	97.4
MG	1.1259	1.1259	1.1261	0.0492	0.0492	26.4	27.2
MG(inf)	0.9999	0.9999	0.9999	0.0003	0.0003	99.5	99.5

NOTE: POLS = Pooled Ordinary Least Squares; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Squares; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); N =50, T= 30; 1000 iteration; Average β = 1.000; RMSE = Root Mean Square Error.

Table 4.3: Performance Comparison (Case II – Heterogeneous Trends)

ESTIMATOR	B&E (2013)	MEAN Replication (GAUSS) Version 9	MEAN Replication (GAUSS) Version 16	RMSE Replication (GAUSS) Version 9	RMSE Replication (GAUSS) Version 16	COVERAGE RATE Replication (GAUSS) Version 9	COVERAGE RATE Replication (GAUSS) Version 16
POLS	0.9731	0.9764	0.9741	0.0940	0.0928	29.1	29.4
2WFE	1.0277	1.0323	1.0332	0.0420	0.0422	40.7	39.5
CCEP	0.9991	0.9978	0.9997	0.0015	0.0016	90.2	87.5
FD-OLS	1.0025	1.0022	1.0016	0.0008	0.0008	92.4	91.5
FE(inf)	0.9998	0.9976	0.9984	0.0018	0.0018	77.6	77
CCEMG	0.9997	0.9976	0.9985	0.0016	0.0017	96.9	96.2
AMG(i)	1.0049	1.0026	1.0027	0.0006	0.0007	98.5	97.9
AMG(ii)	1.0090	1.0015	1.0019	0.0010	0.0010	99.1	98.6
MG	1.1269	1.1259	1.1261	0.0492	0.0492	26.4	27.2
MG(inf)	1.0017	0.9982	0.9986	0.0018	0.0018	97.1	97.1

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Squares; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); N =50, T= 30; 1000 iteration; Average β = 1.000; RMSE = Root Mean Square Error.

Table 4.4: Performance Comparisons (Case III – Feedback)

ESTIMATOR	***MEAN***			***RMSE***		***COVERAGE RATE***	
	B&E (2013)	***Replication (GAUSS)***		***Replication (GAUSS)***		***Replication (GAUSS)***	
		Version 9	***Version 16***	***Version 9***	***Version 16***	***Version 9***	***Version 16***
POLS	0.9754	0.9754	0.9758	0.0457	0.0443	29.2	29.7
2WFE	1.0299	1.0299	1.0293	0.0079	0.0079	46.9	46.8
CCEP	0.9867	0.9867	0.9874	0.0008	0.0008	86.5	86.7
FD-OLS	0.9149	0.9149	0.9143	0.0079	0.0081	6.9	6.7
FE(inf)	0.9924	0.9924	0.9929	0.0004	0.0004	87.9	88.9
CCEMG	0.9828	0.9828	0.9829	0.0009	0.0009	96.4	96.4
AMG(i)	0.9552	0.9552	0.9552	0.0027	0.0028	73.4	72.3
AMG(ii)	0.9511	0.9511	0.9511	0.0031	0.0031	64.7	65.3
MG	1.1157	1.1157	1.1158	0.0458	0.0456	27.7	28.4
MG(inf)	0.9888	0.9888	0.9889	0.0004	0.0004	99.2	99.1

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Squares; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); N =50, T= 30; 1000 iteration; Average β = 1.000; RMSE = Root Mean Square Error.

Table 4.5: Performance Comparisons (Case IV – Beta-Clubs)

ESTIMATOR	*MEAN*			*RMSE*		*COVERAGE RATE*	
	B&E (2013)	*Replication (GAUSS)*		*Replication (GAUSS)*		*Replication (GAUSS)*	
		Version 9	*Version 16*	*Version 9*	*Version 16*	*Version 9*	*Version 16*
POLS	0.5539	0.5539	0.5539	0.3416	0.3442	26.9	26.8
2WFE	1.0224	1.0224	1.0221	0.0194	0.0196	46	46.7
CCEP	1.0017	1.0017	1.0024	0.0015	0.0015	82.1	79.7
FD-OLS	1.0023	1.0023	1.0018	0.0016	0.0017	82.7	82.2
FE(inf)	0.9999	0.9999	1.0013	0.0013	0.0013	72.9	73.5
CCEMG	0.9996	0.9996	0.9996	0.0007	0.0007	100	100
AMG(i)	1.0045	1.0033	1.0034	0.0009	0.0010	100	100
AMG(ii)	1.0132	1.0049	1.0047	0.0011	0.0011	100	100
MG	1.1260	1.1260	1.1262	0.0492	0.0492	51.9	52.8
MG(inf)	1.0000	1.0000	1.0000	0.0003	0.0003	100	100

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Squares; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); N =50, T= 30; 1000 iteration; Average β = 1.000; RMSE = Root Mean Square Error.

Table 4.4 introduces a feedback effect whereby shocks to *y* in turn affect *x* with a one-period lag. As B&E remark, the reason for considering this case is that it "leads to bias in the FD-OLS, which carries over to the AMG estimators: due to differencing the $\varepsilon_{i,t-1}$ are contained in both the errors and the regressors of the FD-OLS estimation equation, whereas this is not the case in the other (levels-based) estimators which account for common factors" (B&E, page 5). This effect on bias for the FD-OLS and AMG estimators is clearly evidenced in the table, as all three estimators now have mean coefficient estimates that are substantially less than 1. As one would expect, this poor performance on bias spills over into coverage rates. In particular, the coverage rates for the FD-OLS estimator are extremely low, less than 10%.

Turning to the other estimators, I see that none of the pooled estimators does particularly well. CCEP is the best of the lot, but it shows slightly more bias than in previous cases, and its coverage rates are worse than before, below 90%. The only estimator that seems to perform well in this environment is the CCEMG estimator. It displays a very slight bias, but its efficiency remains good and its coverage rate is very close to 95%.

The very last case I consider in this analysis is that of "Beta Clubs." The results are reported in Table 4.5. The two pooled estimators, CCEP and FD-OLS, perform well with respect to bias and efficiency. However, coverage rates range between approximately 80 and 83%, so that hypothesis testing would produce an over-rejection of the null hypothesis. The other pooled estimators continue to perform poorly, with the POLS estimator displaying severe bias. The CCEMG, AMG(i), and AMG(ii) estimators perform best among the mean group estimators, but their coverage rates are distorted. Unlike the pooled estimators, they estimate standard errors that are too wide, so that 100% of the 95% confidence intervals contain the true value of the slope coefficient. Note that this is true even for the infeasible MG estimator (MG(inf)). In defence of the estimators, the coverage rates are counted as including the true value when they include 1, and not 0.75 or 2. That is, it is assumed that the econometrician does not know that there are two clubs, and hence makes no effort to assign cross-sectional units to different groups. Thus the confidence intervals and associated null hypotheses can be viewed as misspecified, and so it is not surprising that coverage rates should deviate greatly from 95%.

Before proceeding to additional simulations, it is good to summarize my results so far. Over all four experimental scenarios (Baseline, Heterogeneous Trends, Feedback, Beta Clubs), no single estimator was found to perform "relatively good" in every case. However, several estimators generally performed well, especially if one considers that the coverage rates for the Beta Clubs case are "misspecified." Among the pooled estimators, CCEP performed well on the dimensions of bias and efficiency, though it tended to produce standard errors that were biased downwards, causing coverage rates to sometimes fall below 90%, but not by a large amount. Among the mean group estimators, CCEMG performed best. It consistently produced mean values of the slope coefficient close to 1, had relatively small RMSE values, and generally produced relatively good coverage rates. The one case where it did not perform well on coverage rates was the Beta Clubs case. As noted above, this is somewhat unfair because coverage rates in this case were calculated with respect to the mean value of β (=1), rather than the individual true values of 0.75 and 2.

4.4. Simulation II: Replication and Extension of Bond and Eberhardt (2013a) for specific N & T Dimensions

4.4.1 Data Generating Process (DGP) Set-up

This subsection reproduces the general experimental design from the previous subsection but analyses estimator performance across different N and T values. The goal is to choose estimators for application in the next chapter when I will estimate datasets for "fragile" African countries (N=28 and T=21), "non-fragile" African countries (N=23 and T=21), and for all African countries (N=51 and T=21). The best performing estimator(s) will be used to estimate the income elasticity of health care spending in Chapter 5. To address the wider range of RMSE values that I will encounter, I add another category to the table of performance criteria, "Relatively Very Bad". Estimators for which RMSE is larger than 0.1000 will be colour-coded brown (see Table 4.6 below).

Table 4.6: Revised Performance Criteria

	RMSE	***COVERAGE RATE (= CVR)***
Relatively Good (Green)	RMSE ≤ 0.0050	0.90 ≤ CVR ≤ 0.99
Relatively Neutral (White)	0.0050 < RMSE ≤ 0.0100	(i) 0.85 ≤ CVR < 0.90 (ii) 0.99 < CVR < 1.00
Relatively Bad (Red)	0.0100 < RMSE ≤ 0.1000	(i) CVR < 0.85 (ii) CVR = 1.00
Relatively Very Bad (Brown)	RMSE > 0.1000	---

4.4.2 Simulation Results

Results of the Monte Carlo experiments for panel datasets with dimensions N=28 and T=21 ("Fragile States") are reported in Tables 4.7-4.10, where Cases I through IV are sequentially analysed. Tables 4.11-4.14 report results for datasets having dimensions N=23 and T=21 ("Non-Fragile States"), and Tables 4.15-4.18 do the same for datasets with dimensions N=51 and T=21 ("All States"). All the results use Version 16 of GAUSS.

Having already discussed the individual estimators' performances in Tables 4.2-4.5, it is not necessary to give a detailed discussion of the results from Tables 4.7-4.18. In the preceding section, I determined that the CCEP and the CCEMG estimators generally performed better than the other estimators. My interpretation of Tables 4.7-4.18 is that this conclusion is largely confirmed.

While there are instances where other estimators perform as well or slightly better on some dimensions – for example, among pooled estimators, see FD-OLS in Table 4.8; among mean group estimators, see the AMG estimators in Table 4.7 – these estimators also have instances where they perform poorly.

For example, in Table 4.9, the FD-OLS estimator is more biased than the CCEP estimator, has a substantially higher RMSE, and a coverage rate under 50%. Likewise, in the same table, both AMG estimators show greater bias, lower efficiency, and poorer coverage rates than the CCEMG estimator. Thus, while changing the dimensions of the datasets causes some modification of the respective estimators' performances, the overall conclusion remains the same at this point: The CCEP and CCEMG produce the most reliable results across a wide variety of testing environments, including datasets having the same dimensions as those I will analyse in Chapter 5.

Up to this point in my simulation studies, I have stayed within the parameter settings established by B&E. In the next, and final, set of simulation experiments, I modify the testing environment to try and get closer to the characteristics of the data I will be analysing in my final chapter.

Table 4.7: Performance Comparisons
(Case I -- Baseline, N=28, T=21, "Fragile States")

ESTIMATOR	*MEAN*	*RMSE*	*COVERAGE RATE*
POLS	1.1121	0.1074	29.8
2WFE	1.0491	0.0111	61.2
CCEP	1.0016	0.0016	93.2
FD-OLS	1.0065	0.0020	90.7
FE(inf)	1.0022	0.0009	92.7
CCEMG	1.0026	0.0017	96.9
AMG(i)	1.0076	0.0017	95.6
AMG(ii)	1.0058	0.0017	95.0
MG	1.1240	0.0440	39.2
MG(inf)	1.0020	0.0010	99.0

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.8: Performance Comparisons
(Case II – Heterogeneous Trends, N=28, T=21, "Fragile States")

ESTIMATOR	*MEAN*	*RMSE*	*COVERAGE RATE*
POLS	1.1059	0.1947	32.1
2WFE	1.0457	0.0387	58.1
CCEP	1.0017	0.0033	90.1
FD-OLS	1.0064	0.0021	91.9
FE(inf)	1.0022	0.0031	83.9
CCEMG	1.0024	0.0035	96.0
AMG(i)	1.0075	0.0017	95.8
AMG(ii)	1.0052	0.0026	97.3
MG	1.1240	0.0440	39.2
MG(inf)	1.0014	0.0033	97.1

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.9: Performance Comparisons
(Case III – Feedback, N=28, T=21, "Fragile States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	1.1121	0.1074	29.8
2WFE	1.0438	0.0104	62.6
CCEP	0.9832	0.0019	89.1
FD-OLS	0.9192	0.0086	42.3
FE(inf)	0.9900	0.0010	91.2
CCEMG	0.9794	0.0021	96.0
AMG(i)	0.9608	0.0033	85.7
AMG(ii)	0.9553	0.0037	80.5
MG	1.1090	0.0396	42.3
MG(inf)	0.9851	0.0012	97.9

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.10: Performance Comparisons
(Case IV – Beta Clubs, N=28, T=21, "Fragile States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	1.3687	0.4099	49.8
2WFE	1.0979	0.0349	53.4
CCEP	1.0203	0.0033	86.4
FD-OLS	1.0279	0.0041	83.2
FE(inf)	1.0205	0.0027	81.8
CCEMG	1.0193	0.0017	100
AMG(i)	1.0240	0.0021	100
AMG(ii)	1.0269	0.0024	100
MG	1.1411	0.0440	70.9
MG(inf)	1.0190	0.0010	99.5

POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.11: Performance Comparisons
(Case I – Baseline, N=23, T=21, "Non-Fragile States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	0.9631	0.1094	34.1
2WFE	1.0008	0.0021	92.7
CCEP	1.0014	0.0018	93.1
FD-OLS	1.0007	0.0026	88.6
FE(inf)	1.0020	0.0011	94.8
CCEMG	1.0018	0.0020	97.3
AMG(i)	1.0005	0.0020	92.5
AMG(ii)	1.0012	0.0021	89.5
MG	1.1238	0.0500	36.7
MG(inf)	1.0016	0.0011	98.2

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.12: Performance Comparisons
(Case II – Heterogeneous Trends, N=23, T=21, "Non-Fragile States")

ESTIMATOR	*MEAN*	*RMSE*	*COVERAGE RATE*
POLS	0.9705	0.2190	33.1
2WFE	0.9971	0.0165	89.1
CCEP	1.0016	0.0033	91.2
FD-OLS	1.0008	0.0026	89.8
FE(inf)	0.9998	0.0040	83.1
CCEMG	1.0017	0.0038	96.0
AMG(i)	1.0005	0.0020	92.3
AMG(ii)	1.0021	0.0026	97.5
MG	1.1238	0.0500	36.7
MG(inf)	0.9999	0.0042	96.2

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.13: Performance Comparisons
(Case III – Feedback, N=23, T=21, "Non-Fragile States")

ESTIMATOR	*MEAN*	*RMSE*	*COVERAGE RATE*
POLS	0.9631	0.1093	34.0
2WFE	0.9942	0.0020	92.6
CCEP	0.9825	0.0021	91.0
FD-OLS	0.9079	0.0111	39.4
FE(inf)	0.9896	0.0012	93.5
CCEMG	0.9785	0.0023	95.1
AMG(i)	0.9475	0.0048	74.5
AMG(ii)	0.9448	0.0051	71.0
MG	1.1089	0.0451	39.7
MG(inf)	0.9855	0.0013	98.7

POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.14: Performance Comparisons
(Case IV – Beta Clubs, N=23, T=21, "Non-Fragile States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	2.401	1.9063	0
2WFE	1.0188	0.0099	87.3
CCEP	1.0208	0.0040	84.0
FD-OLS	1.0198	0.0054	82.0
FE(inf)	1.0220	0.0029	85.0
CCEMG	1.0233	0.0020	100.0
AMG(i)	1.0209	0.0027	100.0
AMG(ii)	1.0262	0.0031	100.0
MG	1.1453	0.0500	71.0
MG(inf)	1.0231	0.0011	100.0

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.15: Performance Comparisons
(Case I – Baseline, N=51, T=21, "All States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	0.9603	0.0527	33.6
2WFE	1.0015	0.0009	92.2
CCEP	1.0017	0.0008	93.1
FD-OLS	1.0019	0.0012	88.1
FE(inf)	1.0014	0.0005	94.1
CCEMG	1.0019	0.0008	98.0
AMG(i)	1.0011	0.0009	94.0
AMG(ii)	1.0018	0.0009	91.8
MG	1.1257	0.0502	25.6
MG(inf)	1.0011	0.0005	98.9

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.16: Performance Comparisons
(Case II – Heterogeneous Trends, N=51, T=21, "All States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	0.9755	0.1034	33.9
2WFE	1.0006	0.0075	88.1
CCEP	1.0017	0.0016	90.9
FD-OLS	1.0019	0.0012	89.6
FE(inf)	1.0021	0.0018	84.5
CCEMG	1.0016	0.0018	96.6
AMG(i)	1.0011	0.0009	94.0
AMG(ii)	1.0016	0.0013	97.1
MG	1.1257	0.0502	25.6
MG(inf)	1.0018	0.0020	97.0

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.17: Performance Comparisons
(Case III – Feedback, N=51, T=21, "All States")

ESTIMATOR	***MEAN***	***RMSE***	***COVERAGE RATE***
POLS	0.9603	0.0527	33.7
2WFE	0.9944	0.0009	92.1
CCEP	0.9820	0.0011	88.5
FD-OLS	0.9086	0.0094	13.4
FE(inf)	0.9887	0.0006	91.3
CCEMG	0.9776	0.0013	94.3
AMG(i)	0.9490	0.0035	57.5
AMG(ii)	0.9462	0.0038	51.5
MG	1.1105	0.0453	28.0
MG(inf)	0.9846	0.0007	97.8

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

Table 4.18: Performance Comparisons
(Case IV – Beta Clubs, N=51, T=21, "All States")

ESTIMATOR	*MEAN*	*RMSE*	*COVERAGE RATE*
POLS	-0.0654	1.1272	0.0
2WFE	0.9959	0.0041	86.7
CCEP	0.9965	0.0017	84.8
FD-OLS	0.9975	0.0022	81.2
FE(inf)	0.9961	0.0012	86.9
CCEMG	0.9971	0.0008	100
AMG(i)	0.9997	0.0110	100
AMG(ii)	0.9999	0.0012	100
MG	1.1210	0.0502	51.5
MG(inf)	0.9965	0.0005	100

NOTE: POLS = Pooled Ordinary Leasy Square; 2WFE = Two-Way Fixed Effects; CCEP = Common Correlated Effect Pooled Estimator; FD-OLS = First Difference Ordinary Least Square; FE(inf) = Infeasible Fixed Effect (FE augmented with common unobservable factors); CCEMG = Common Correlated Effect Mean Group; AMG = Augmented Mean Group Estimator; MG = Mean Group Estimator; MG(inf) = Infeasible Mean Group (MG augmented with common unobservable factors); RMSE = Root Mean Square Error.

4.5 Conclusion

This chapter examined the performance of standard panel data estimators (such as POLS, FE, 2WFE, and FD-OLS) in the presence of slope heterogeneity, cross-sectional dependence, non-stationarity of observable and unobservable variables, and endogeneity. I compared the performance of these pooled type estimators with more recently developed, mean group type estimators such as MG, CCEMG, and AMG.

All the estimators were assessed using the general experimental design employed in Bond and Eberhardt (2013a), henceforth B&E, who graciously provided me their code. I made a number of extensions and modifications to their code for my analysis. I conducted three sets of simulation experiments. The first experiment replicated the original paper and extended it by adding additional performance metrics for efficiency and coverage rates. The second set of experiments reproduced the first set of experiments, but with different panel data dimensions (N and T) to better simulate the kinds of datasets I will be analysing in my next chapter.

The purpose of undertaking these experiments was to identify the "best" estimator(s) for analysing the income elasticity of health care expenditures for selected African countries, the subject of my next chapter. I conclude on the basis of my experiments that, overall, the CCEMG estimator is the "best" on the dimensions of bias, efficiency, and coverage rates. However, it was not best in all circumstances. In particular, coverage rates for the CCEMG were distorted when cross-sectional units were characterized by "beta clubs." Further, CCEMG had poor efficiency performance when the influence of the shared common factor ($f_{2,t}$ in the notation used above) was minimized in Tables 4.19-4.22. As a result, my analysis next chapter will include a selection of other pooled type (POLS and 2WFE) and mean group type (AMG(i)) estimators as robustness checks.

Chapter 5: Health Expenditure and Income in Africa: Evidence from Heterogeneous Panel Data Estimators

Chapter Five

5.1 Introduction

5.1.1 Preamble

In this chapter, I consider income as a key factor influencing changes in health expenditure across countries. Despite the plethora of empirical evidence on the nexus between health spending and income as cited in Costa-Font et al. (2011), most of the studies are for developed countries with very few papers on developing nations, especially African countries. In this study, I therefore use a cross-sectional time series dataset for African countries to determine the "income elasticity of health expenditure" using newly developed panel data estimators (examined in Chapter 4). The outcomes from the simulation experiments in Chapter 4 are used as a guide in selecting the appropriate econometric methods for testing whether health is a "luxury" or a "necessity" good in Africa.

5.1.2 Overview

Health expenditure is a metric that quantifies the current purchases of health goods and services for final consumption. The expenditure on health is from both public and private sources and pays for medical goods and services, public health and prevention programmes, and administration (OECD, 2016). Spending on health is naturally bound by budget constraints such as the current and expected income level. Policy makers around the world worry about rising health care spending – often for the following reasons.

First, an increasing share of health spending is financed by the public sector and paid through taxes (Gerdtham & Jönsson, 2000a). Raising taxes to finance health care bills can escalate concerns among tax payers and also increase the demand for health care services by tax payers (Leu (1986). This is particularly pressing in times of increasing budget deficits (OECD, 2016).

Another issue concerns the relationship between public and private spending levels. Bird (1970) argues that public financing of health care services crowds out private spending to the extent that it lowers the overall spending on health. Pryor (1968, p. 171) also concludes that public and private health expenditures are close substitutes.

As a complication for analytical purposes, health spending is likely to exhibit strong path dependence. Increased health expenditures lead to better health outcomes and better current health outcomes may, in turn, reduce future health spending (Kleiman (1974, p. 67). Also, the stock of health and expenditure on health-augmenting consumption (such as better diets, better quality housing, etc.) are positively related to income. The substitution and income effects can increase the level of health consumption relative to income. Many studies take this view (see Bunn, LeRoux, Reinold, & Surico, 2017; Carroll, 1994; Christelis, Georgarakos, Jappelli, Pistaferri, & van Rooij, 2017; Hau & Mishkin, 1982; Roberts, 2000; Selvanathan & Selvanathan, 1993).

Whatever the mechanism, there is general agreement that income is a strong predictor of health care spending (Culyer (1988, 1989a, 1989b), Newhouse and Phelps (1974), Newhouse (1977) and there is a general consensus that the share of income expended on health care services rises as a country’s per capita income increases (Baltagi, Lagravinese, Moscone, & Tosetti, 2016; Hall & Jones, 2007). However, there is still conflicting evidence on the degree (or magnitude) of the responsiveness of health care expenditures to changes in per capita income. Studies reviewed in Culyer (1988), Gerdtham and Jönsson (2000a), and Costa-Font et al. (2011) have examined the income elasticity of health expenditure with the goal of establishing whether health is a “luxury” (i.e., with income elasticity greater than one) or a “necessity” (income elasticity less than one).

The determination of the income elasticity of health expenditure has two major policy implications. First, according to Culyer (1988), if health care is a necessity good, more government involment through financing is encouraged in order to reduce the financial burden placed on households, especially in poor countries with low per capita income. If health is a luxury good, out-of-pocket spending and private insurance coverage (both as components of private health expenditures) should account for a larger share of total health spending and be used as a partial subsitute for public healthcare spending to reduce budget deficits.

Second, ascertaining the size of the elasticity coefficient helps to understand the nature of -- and the reasons for -- the demand for healthcare services. According to Newhouse (1977), when health care is a luxury good, the demand may relate more to preventation or caring; when it is a necessity good, it may reflect curing of life threatening diseases. The latter type is common in developing countries (see Gerdtham & Jönsson, 2000a, p. 22; V. N. R. Murthy & A. A. Okunade, 2009).

A wide range of elasticity coefficients have been reported in the literature. Several factors can contribute to the differences in the documented outcomes. These include: biases in aggregating components of health expenditure (Costa-Font et al., 2011), use of different datasets (Getzen, 2000), adoption of different econometric methods (Chakroun, 2010; Gerdtham & Jönsson, 2000a, p. 20), model misspecification (McGuire, Parkin, Hughes, & Gerard, 1993), spurious relationships and wrong modelling of non-stationary variables, cross-sectionally correlated and cointegrated health-income variables (Baltagi & Moscone, 2010; Hansen & King, 1996, 1998; Okunade & Karakus, 2001), assumptions about homogeneity or heterogeneity of the elasticity coefficient across countries (Baltagi et al., 2016; Baltagi & Moscone, 2010), neglecting to account for unobservable common health shocks (Moscone & Tosetti, 2010), and failure to address endogeneity[31]. These issues are discussed in detail in

[31] In recent literature such as Barro (2013) a two to three-way nexus among income, health spending and health outcome has been acknowledged but treating one or two of the variables as endogenous is rare. In this chapter, I present a novel approach by using modern panel data estimators to account for endogeneity emanating from health expenditure being a predictor of income and health outcomes. Unobservable common health risk factors and geographical patterns of diseases across countries constitute another potential sources of endogeneity. The latter source is discussed in detail below.

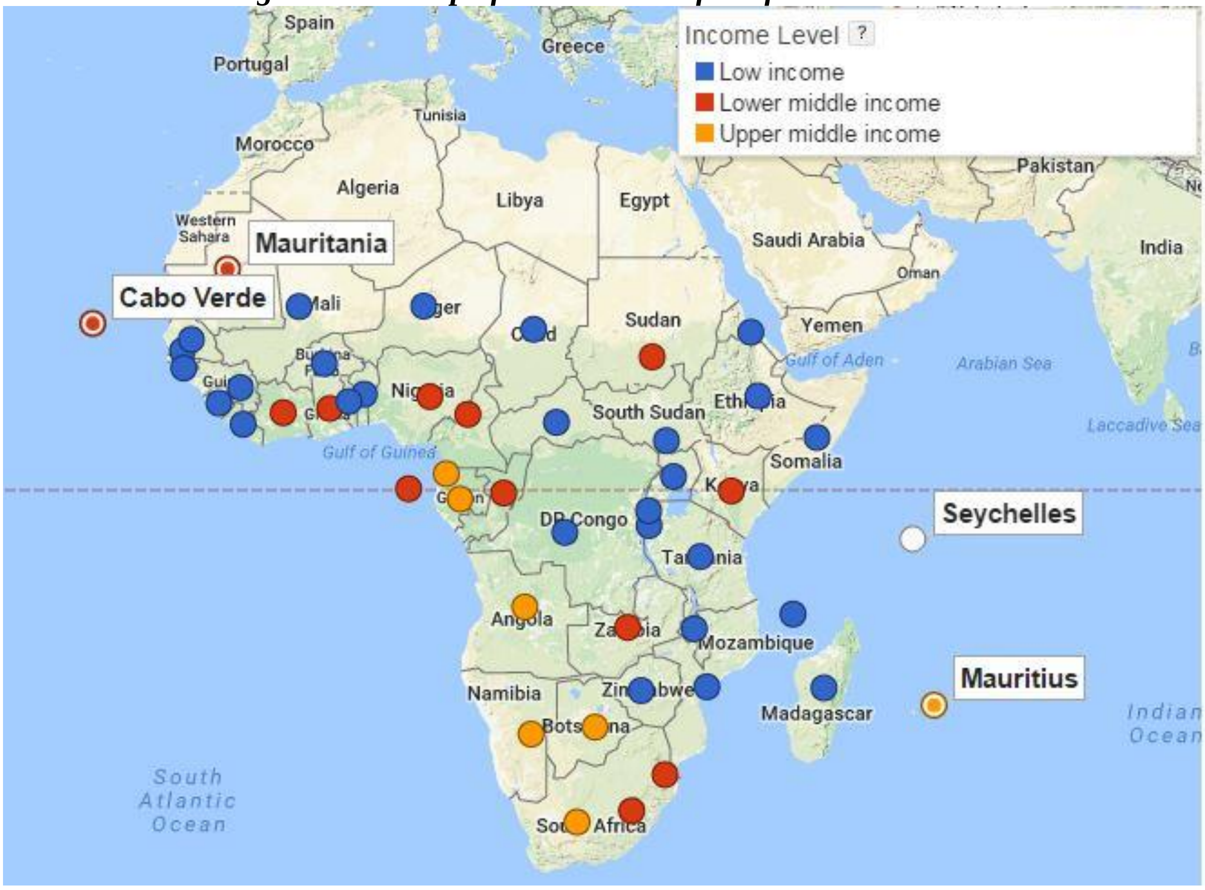
subsequent sections and an effort is made to address the problems using novel estimation approaches.

Another important but neglected area is the differential degree of responsiveness of private vs. public health expenditure to changes in income. This difference has also contributed to the conflicting outcomes regarding whether the income elasticity is greater or less than unity (see Gerdtham & Jönsson, 2000a, p. 23). The share of private health expenditure in total medical expenditure varies widely across countries. The variation can reflect a country's level of development, income per capita growth, and attitudes towards equity. In countries with relatively high incomes (such as the OECD and transitional economies of Europe), there tends to be significant government involvement in financing healthcare expenses (Newhouse, 1977), compared to low income countries such as India, many Asian countries, and – importantly for the purposes of this chapter – countries in Sub-Saharan Africa (see Gerdtham & Jönsson, 2000a, p. 15).

5.2 Health and Income in Africa: Stylized Facts

The African continent is lagging behind in the attainment of health related Millennium Development Goals (MDGs) (OECD, 2014). For example, the African region accounts for 90% of globally reported malaria deaths with the highest incidence among under-5 year-old children (WHO, 2014). In 2014, based on World.Bank (2015) estimates for African countries (see Table 5.1), the average life expectancy at birth stood at 61.2 years and 50% of the countries were below the group average. Africa is dominated by low income countries (see Figure 5.1) struggling to mobilise revenue domestically due to high poverty prevalence and deteriorating human welfare (see OECD, 2014; WHO, 2014; World.Bank, 2015).

Figure 5.1[32]: Map of Income Level for African Countries



Official Development Assistance (ODA) and remittances account for a major share of government spending on health care. Estimates from the WHO (2014) Global Health Observatory (GHO) indicate that ODA disbursement for health per capita in the African region increased by 263% between 2002 and 2010 -- from US$2.7 to US$9.8. Over 50% of the disbursement for health in 2010 was committed in MDG 6 - combat of HIV/AIDS, malaria and other diseases. These economic and social challenges are more severe for countries faced with civil war and political crises. These are countries categorised as fragile states and defined by “deep structural economic and political constraints” (Maier, 2010). Some of the analyses in this chapter focus on a subset of countries classified as fragile and conflict-affected African (FCA) states.

[32] http://bit.ly/2mJ1FNZ

Across our overall sample (see Table 5.1), 6% of GDP was allocated by the public and private sector for health spending in 2014 (THEG). There is a slight difference in the public (PHT, 50.3%) and private (OTHE, 34.2%) sector share of total health expenditure, while out-of-pocket expenditure as a share of total private health spending is around 68.4% (OPRE).

African countries with higher income spend more on healthcare service provisions (see Figure 5.2). Looking beyond income, the amount a particular country spends on medical services and the rate at which it grows over time can be the result of economic, social and political factors, as well as the financing and organisational structure of the country's health system (OECD, 2015). Some of the plausible factors that explain the presented plot in Figure 5.2 for sampled African countries are identified and described in subsequent sections.

Table 5.1: Macroeconomic Indicators of African Countries (2014 Estimates)

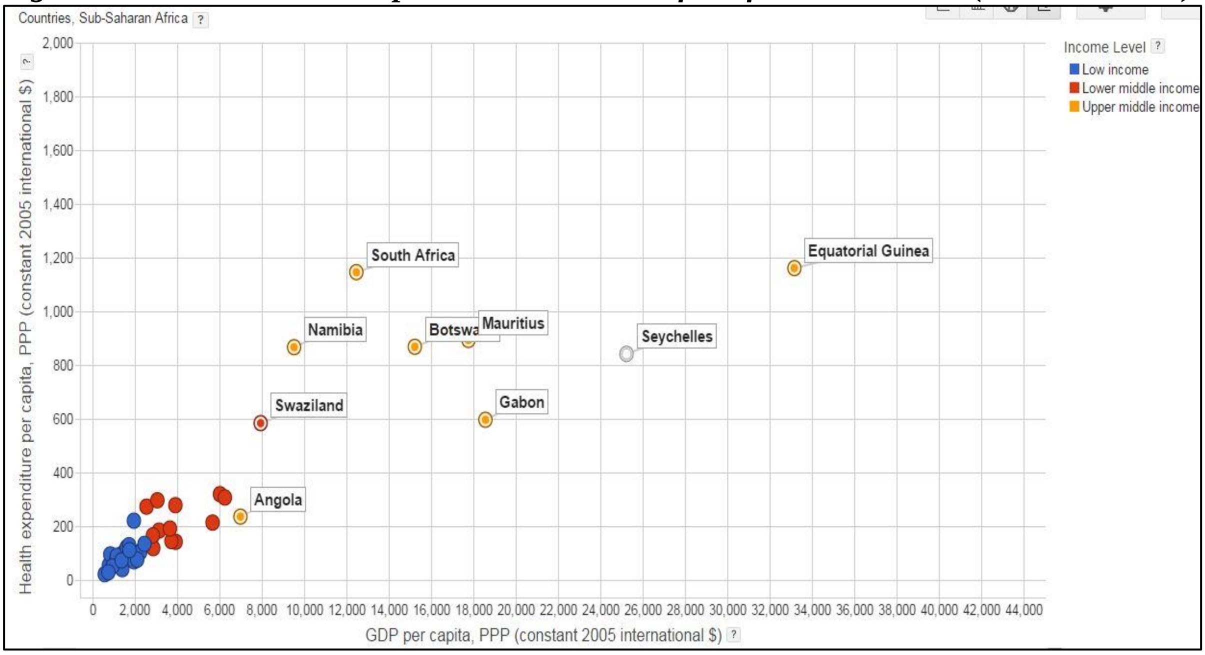
No.	*Country*	*THEG*	*PHT*	*OTHE*	*OPRE*	*GDPG*	*ODA*	*LEX*	*P15*	*P65*
1	***Algeria***	7.2	72.8	26.5	97.3	1.8	4.0	74.8	28.2	5.8
2	***Angola***	3.3	64.3	24.0	67.0	1.4	9.5	52.3	47.9	2.3
3	***Benin***	4.6	49.0	39.1	76.7	3.6	56.2	59.5	42.5	2.9
4	***Botswana***	5.4	59.0	5.2	12.7	1.2	44.4	64.4	32.2	3.5
5	***Burkina Faso***	5.0	52.3	39.1	81.9	1.0	63.4	58.6	45.8	2.4
6	***Burundi***	7.5	52.7	21.0	44.5	1.3	46.1	56.7	44.6	2.5
7	***Cabo Verde***	4.8	74.7	22.2	88.0	0.5	445.7	73.1	30.0	4.7
8	***Cameroon***	4.1	22.9	66.3	86.0	3.3	37.0	55.5	42.8	3.2
9	***Central African Republic***	4.2	49.0	46.2	90.6	-0.9	126.4	50.7	39.4	3.9
10	***Chad***	3.6	54.6	39.2	86.3	3.4	28.4	51.6	48.0	2.5
11	***Comoros***	6.7	32.9	45.1	67.1	-0.4	95.8	63.3	40.5	2.8
12	***Congo, Dem. Rep.***	4.3	36.9	38.8	61.5	5.6	31.7	58.7	46.2	3.0
13	***Congo, Rep.***	5.2	81.8	17.5	96.0	4.2	23.4	62.3	42.6	3.6

No.	Country	THEG	PHT	OTHE	OPRE	GDPG	ODA	LEX	P15	P65
14	***Cote d'Ivoire***	5.7	29.4	50.8	71.9	5.9	41.4	51.6	42.7	3.0
15	***Djibouti***	10.6	63.9	35.8	99.2	4.6	186.9	62.0	33.0	4.1
16	***Egypt, Arab Rep.***	5.6	38.2	55.7	90.1	0.0	39.2	71.1	33.0	5.2
17	***Equatorial Guinea***	3.8	77.1	20.1	87.9	-3.6	0.7	57.6	39.4	2.9
18	***Eritrea***	3.3	45.8	54.2	100.0	---	---	63.7	---	---
19	***Ethiopia***	4.9	58.7	32.3	78.1	7.5	36.5	64.0	42.1	3.5
20	***Gabon***	3.4	68.4	21.9	69.2	2.0	65.7	64.4	37.3	5.2
21	***Gambia, The***	7.3	68.7	17.0	54.5	-2.3	51.0	60.2	46.3	2.3
22	***Ghana***	3.6	59.8	26.8	66.8	1.6	41.8	61.3	38.9	3.4
23	***Guinea***	5.6	48.5	45.3	88.0	-2.3	45.7	58.7	42.7	3.1
24	***Guinea-Bissau***	5.6	20.5	49.5	62.2	0.1	60.3	55.2	41.0	3.1
25	***Kenya***	5.7	61.3	26.1	67.4	2.6	58.8	61.6	42.1	2.8
26	***Lesotho***	10.6	76.1	16.5	69.0	3.2	48.8	49.7	36.3	4.2
27	***Liberia***	10.0	31.5	30.7	44.8	-1.7	169.2	60.8	42.6	3.0
28	***Libya***	5.0	73.5	26.5	100.0	----	33.1	71.7	29.7	4.5
29	***Madagascar***	3.0	48.4	41.4	80.2	0.5	24.6	65.1	42.0	2.8
30	***Malawi***	11.4	52.7	10.6	22.5	2.5	55.5	62.7	45.4	3.4
31	***Mali***	6.9	22.9	47.7	61.8	3.9	72.2	58.0	47.5	2.6
32	***Mauritania***	3.8	49.6	43.8	87.0	1.7	64.8	63.0	40.3	3.2
33	***Mauritius***	4.8	49.2	46.4	91.3	3.6	38.6	74.2	19.8	9.1
34	***Morocco***	5.9	33.9	58.4	88.3	1.1	65.7	74.0	27.3	6.1
35	***Mozambique***	7.0	56.4	9.5	21.8	4.5	77.0	55.0	45.5	3.3
36	***Namibia***	8.9	60.0	7.2	17.9	4.0	93.0	64.7	36.9	3.5

No.	*Country*	*THEG*	*PHT*	*OTHE*	*OPRE*	*GDPG*	*ODA*	*LEX*	*P15*	*P65*
37	***Niger***	5.8	55.2	34.3	76.7	2.8	47.8	61.5	50.4	2.6
38	***Nigeria***	3.7	25.1	71.7	95.7	3.5	13.7	52.8	44.1	2.7
39	***Rwanda***	7.5	38.1	28.1	45.4	4.5	90.3	64.0	41.4	2.7
40	***Sao Tome and Principe***	8.4	43.2	11.2	19.7	4.0	206.7	66.4	42.9	3.2
41	***Senegal***	4.7	51.8	37.3	77.4	1.1	75.2	66.4	43.8	3.0
42	***Seychelles***	3.4	92.2	2.3	30.0	1.6	106.1	73.2	23.2	6.8
43	***Sierra Leone***	11.1	17.0	61.0	73.4	2.3	139.7	50.9	42.7	2.7
44	***Somalia***	---	---	---	---	---	105.1	55.4	46.9	2.8
45	***South Africa***	8.8	48.2	6.5	12.5	0.0	19.6	57.2	29.5	5.0
46	***South Sudan***	2.7	41.5	54.2	92.6	-0.6	163.3	55.7	42.4	3.5
47	***Sudan***	8.4	21.4	75.5	96.1	0.5	22.0	63.5	40.9	3.3
48	***Swaziland***	9.3	75.7	10.3	42.4	1.3	67.0	48.9	37.6	3.5
49	***Tanzania***	5.6	46.4	23.2	43.3	3.6	50.7	64.9	45.2	3.2
50	***Togo***	5.2	38.4	46.2	75.1	3.1	29.1	59.7	42.4	2.8
51	***Tunisia***	7.0	56.7	37.7	87.1	1.8	84.6	74.1	23.3	7.5
52	***Uganda***	7.2	24.9	41.0	54.6	1.8	42.9	58.5	48.3	2.5
53	***Zambia***	5.0	55.3	30.0	67.2	1.5	62.6	60.0	46.1	2.9
54	***Zimbabwe***	6.4	38.3	35.9	58.3	1.5	48.9	57.5	41.6	3.0
	Average	6.0	50.3	34.2	68.4	2.0	70.9	61.2	39.9	3.6

NOTE: THEG = Health expenditure, total (% of GDP); PHT = Health expenditure, public (% of total health expenditure); OTHE = Out-of-pocket health expenditure (% of total expenditure on health); OPRE = Out-of-pocket health expenditure (% of private expenditure on health); GDPG = GDP per capita growth (annual %); ODA = Real net official development assistance and official aid received per capita (constant 2013 US$); LEX = Life expectancy at birth, total (years); P15 = Population ages 0-14 (% of total); P65 = Population ages 65 and above (% of total). Source: World.Bank (2017).

Figure 5.2[33]: Total Health Expenditure vs. Income for African Countries (2014 Estimates)



As discussed in the next section, this study contributes to the existing literature on the determinants of health care expenditure in a number of ways. This includes: (i) examining the income elasticity of public and private healthcare expenditure in a baseline framework; (ii) assessing the robustness of the baseline analyses to changes in model specification, estimation methods, and datasets decomposed by country's fragility[34] status, income group[35], and region[36].

5.3 Empirical Review

Numerous studies have been conducted on the health-income nexus over the past four decades, following the seminal contributions by Grossman (1972a) and Newhouse and Phelps (1974). The macro-level attention paid to the relationship between health expenditure and income, mostly for OECD countries, can be traced back to earlier works of Kleiman (1974) and Newhouse (1977). Income has been one of the key factors believed to explain variation in

[33] http://bit.ly/2n8Zb8K
[34] Classification based on OECD (2014) Fragile States Index
[35] World Bank (2017) income group classification
[36] World Bank (2017) regional classification of Africa into Central, Northern, Western, Eastern, and Southern regions

the level of health expenditure across countries (Costa-Font et al., 2011; Gerdtham & Jönsson, 2000b; Kea, Saksenaa, & Hollyb, 2011; V. N. R. Murthy & A. A. Okunade, 2009).

Previous studies can be categorised into three major groups. The first group of studies (Barros, 1998; Clemente, Marcuello, Montañés, & Pueyo, 2004; Farag et al., 2012; Gerdtham & Jönsson, 1992; Getzen, 2000; Hitiris, 1997; Jaunky & Khadaroo, 2008; Liu, Li, & Wang, 2011; Mehrara, Musai, & Amiri, 2010; Newhouse, 2006) corroborate the "*luxury good hypothesis*" of income elasticity of health expenditure greater than one. The second group (Baltagi & Moscone, 2010; Å. G. Blomqvist & R. A. Carter, 1997; Culyer, 1988; Di Matteo, 2003; Farag et al., 2012; Hitiris & Posnett, 1992; Lv & Zhu, 2014; Parkin, McGuire, & Yule, 1987; Sen, 2005) conclude that health is a "*necessity good*" with income elasticity less than one. This implies that health expenditure responds to changes in income less than proportionally. The last strand of studies (Gbesemete & Gerdtham, 1992; Hitiris & Posnett, 1992; Lago-Peñas, Cantarero-Prieto, & Blázquez-Fernández, 2013; Murthy & Ukpolo, 1994) conclude that the response of health expenditure to income change is proportional, i.e., *income elasticity is unity*.

In a meta-analysis investigation by Costa-Font et al. (2011) for 167 studies, income elasticity ranging from 0.4 to 0.8 was found, refuting the hypothesis that health care is a luxury good. They concluded that heterogeneity of empirical results among the 167 studies for developed countries might be attributed to publication selection and data aggregation biases. Glaeser, Sacerdote, and Scheinkman (2003) had earlier noted that most of the evidence confirming the "luxury good hypothesis" is based on aggregate or national level datasets. This makes it difficult to draw inference about sectoral, sub-regional or individual behaviour.

Disaggregation of health expenditure into public and private sector components is gradually receiving attention in the literature. Empirical results of such disaggregated analyses have been conflicting. Using cross-sectional data, Schieber and Maeda (1999) found the two forms of expenditure to be income elastic but more so for public health care spending. Musgrove, Zeramdini, and Carrin (2002) reported that the income elasticity of government health expenditure is greater than one, while it is less than one for out-of-pocket (private) health expenditure. Using panel data for 143 countries from 1995 to 2008, Kea et al. (2011) found no significant difference in the income elasticity of public and private health expenditure among developing nations. Contrary to previous findings,J. A. Khan and Mahumud (2015), using panel data for nine South-East Asian Regional (SEAR) countries for the period 1995-2010, found public health expenditure to be income inelastic and private health expenditure elastic. In conclusion, the empirical evidence on the relationship between income and health spending categorised into public and private has been limited in scope and inconsistent.

Furthermore, the dearth of studies on the relationship between total healthcare expenditure and income for African countries is striking. This may be due to data availability as most previous studies employed cross-sectional data (Gbesemete & Gerdtham, 1992; Murthy, 2004; V. N. R. Murthy & A. A. Okunade, 2009; Okunade, 2005) and very few used cross-sectional time series data (Jaunky & Khadaroo, 2008; Lv & Zhu, 2014). All previous studies on Africa except for Jaunky and Khadaroo (2008) conclude that health is a necessity rather than a luxury good (see Table 5.2). Jaunky and Khadaroo (2008) found public health expenditure to be a luxury good and private health expenditure a necessity good.[37]

[37] An extensive review of previous studies on the income elasticity of health expenditure both in developed and developing countries is presented in Table 5.3 in the Appendix.

Table 5.2: Coefficients and Nature of Healthcare Services in Africa (1984-2009)

Author (year)	*Data type*	*Sample Year(s)*	*Number of countries*	*Categorisation of Health Expenditures*	*Estimated Income elasticity*
Gbesemete and Gerdtham (1992)	Cross-sectional	1984	26	Necessity	0.885 – 1.069
Murthy (2004)	Cross-sectional	2001	44	Unity	1.11
Okunade (2005)	Cross-sectional	1995	26	Necessity	0.46 – 0.70
V. N. R. Murthy and A. A. Okunade (2009)	Cross-sectional	2001	30	Necessity	1.089 – 1.118
Jaunky and Khadaroo (2008)	Panel	1991-2000	28	Luxury for public expenditure Necessity for private expenditure	Public (0.929 – 1.21); Private (0.661 – 0.909)
Lv and Zhu (2014)	Panel	1995-2009	42	Necessity	0.758 – 0.988

SOURCE: Author’s compilation.

In this study, updated datasets are employed to identify the determinants of health expenditures in African. To the best of my knowledge, this study is the first to examine the income-health expenditure relationship for the most vulnerable and highly remittance dependent countries in Africa. These countries are characterized by fragility and long-term conflicts (OECD, 2014). The continent has fallen victim to political instability, civil war, devastating violence, religious extremism and xenophobia over the years (see King & Lawrence, 2005 -for a vivid account of civil war and conflicts in Africa from 1960s to early 2000s). These have made it impossible for most of the countries in the region to experience sustainable and inclusive growth. The nonexistence of growth accompanied by poverty reduction, human capital development and good governance has made Africa a fragile region (Arbache & Page, 2010; Maier, 2010).

5.4 Theoretical Framework for Model Specification

There is no formal economic theory to predict the relationship between per capita healthcare expenditure and per capita income (H. N. Khan et al., 2016) or non-income determinants of health spending (Okunade, 2005). Leu (1986) made an attempt to provide a theoretical link between income and public-private mix spending through his public choice framework but it is largely ad hoc. Modelling of the inverse relationship (health expenditures → income) is much better established. In the area of economic growth, there is a well-recognised theory that suggests that investment in health as a component of human capital promotes economic growth (Barro & Sala-i-Martin, 1995). An increase in the stock of physical and human capital determined by health expenditure may cause per capita GDP to rise (Solow, 1956).

Empirically, Fan and Savedoff (2014, p. 114) noted that income is the only factor agreed by most health economists to have a highly significant impact on health spending. Reviewing other previous studies (such as Chernew & Newhouse, 2012; Garibaldi, Martins, &

van Ours, 2010; Hall & Jones, 2007; Martins, Joaquim, & Bjørnerud, 2006; Murthy & Okunade, 2016; Okunade & Murthy, 2002), additional key determinants of health spending include: (i) changes in medical technology and practice; (ii) elderly population growth; (iii) rising prices; and (iv) changes in the financing and management of health care. Some studies (see e.g. Baltagi & Moscone, 2010; Chakroun, 2010; Di Matteo, 2000, 2003, 2005; Dreger & Reimers, 2005; Gerdtham, Søgaard, Andersson, & Jönsson, 1992; Ke et al., 2011; H. N. Khan et al., 2016; J. A. Khan & Mahumud, 2015; Moscone & Tosetti, 2010; Murthy & Okunade, 2000; V. N. R. Murthy & A. A. Okunade, 2009; Murthy & Okunade, 2016; Rivera & Currais, 1999; Roberts, 1999; Sen, 2005) expand this list to also include: population per number of medical personnel; population age structure (under 5, under 15, and 15-64); urbanization; payment system; political transition; the public finance share of GDP; government budget deficits; level of health research and development spending; official development assistance; income inequality; public corruption; political conflicts and internal discords; number of beds, disease patterns (i.e. prevalence of highly infectious diseases such as HIV, malaria, tuberculosis, diabetes, hypertension and cancer); life expectancy; maternal mortality rate; infant mortality rate; and the literacy rate.

Based on the factors identified as important in previous studies of developing countries, my model is specified as follows:

$$\begin{aligned} HCE_{it} = {} & \alpha + \beta_1 GDP_{it} + \beta_2 LEX_{it} + \beta_3 INM_{it} + \beta_4 P65_{it} \\ & + \beta_5 P15_{it} + \beta_6 ODA_{it} + \beta_7 GFC_{it} + \mu_i + \omega_{it} \end{aligned} \tag{5.1}$$

where $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$; i indexes the cross-section dimension (i.e. individual African countries); and t denotes the time period (i.e., annual observations from 1995 to 2014). In country *i* at time t: HCE_{it} is real per capita health expenditure. HCE_{it} is a composite of real per capita: total (THE_{it}), government (GHE_{it}) and out-of-pocket health expenditures (OPE_{it}); GDP_{it} is real per capita gross domestic expenditure as a proxy for real per capita income; LEX_{it} is life expectancy at birth (years); INM_{it} is infant mortality rate at birth; $P65_{it}$ is the percentage of the population aged 65 and above; $P15_{it}$ is the share under 15 years of age; ODA_{it} is per capita real net official development assistance and official aid received; GFC_{it} is total governmental expenditure as a share of GDP (a proxy for government fiscal capacity); α is the common intercept across groups; μ_i is the unobservable country-specific effect; ω_{it} is the error term. The composite one-way error component is defined as: $u_{it} = \mu_i + \omega_{it}$; β_1 is the slope coefficient of GDP and is the income elasticity coefficient of health expenditures[38]; β_{2-7} are parameters for the non-income determinants of healthcare expenditure. All the variables in Equation (5.1) are expressed in natural logarithms.

5.5 Variables Description and Theoretical Expectations

Government and private health expenditures are the two major components of total healthcare expenditure based on the sources of financing medical expenses. According to Ke et al. (2011), the government component of health expenditure consists of payment contributions made through all forms of taxation and insurance (either compulsory or voluntary). Private health expenditure consists of private insurance and out-of-pocket payments. The latter is made by patients at the point of receiving health care services. Each of the components may have a different relationship with the determinants or explanatory variables incorporated in model (5.1). For instance, government fiscal capacity measured as a ratio of total government expenditure to GDP is a metric that reflects the size of government resources. It may increase government health expenditure while reducing out-of-pocket expenditure. Also, Official Development Assistance can reduce household burden by financing

[38] β_1 represents the percentage change in health expenditure resulting from 1% change in income. Health care expenditures are luxury or necessity if, respectively, $\beta_1 > 1$ and $\beta_1 < 1$, indicating that health expenditures increase faster or slower than income (Costa-Font et al., 2011).

private health consumption at the point of receiving treatments, while increasing the level of resources available to the government to finance healthcare services.

The dependent variables according to the World Bank (2017) definition are described as follows:

Total Health Expenditure

Total health expenditure is the sum of per capita public and private health expenditures. It covers the provision of health services (preventive and curative), family planning activities, nutrition activities, and emergency aid designated for health. It does not include provision of water and sanitation.

Government Health Expenditure

Public health expenditure consists of recurrent and capital spending from government (central and local) budgets, external borrowings and grants (including grants and aid from international agencies and nongovernmental organizations), and social (or compulsory) health insurance funds.

Out-of-Pocket Expenditure

Out of pocket expenditure is any direct outlay by households, including gratuities and in-kind payments, to health practitioners and suppliers of pharmaceuticals, therapeutic appliances, and other goods and services whose primary intent is to contribute to the restoration or enhancement of the health status of individuals or population groups.

The mechanism of impact of each of the explanatory variables on health expenditure as documented in previous literature is explained as follows.

GDP as a Measure of Income

In the context of modelling health expenditure and income in Africa, it is expected that the income elasticity coefficient will be less than unity as heath care is demanded more for curative reasons and less for prevention. This is consistent with previous findings (Gbesemete

& Gerdtham, 1992; Lv & Zhu, 2014; V. N. R. Murthy & A. A. Okunade, 2009; Okunade, 2005) for Africa within the last two and half decades.

Life Expectancy

Life expectancy can serve as an indicator to proxy quality of life (Hall & Jones, 2007), advancement in medical technology (Dreger & Reimers, 2005) and changes in disease patterns (Ke et al., 2011). For three decades in the health economics literature, technological progress[39] has been identified to be a positive and significant driver of health expenditure (e.g. A. G. Blomqvist & R. A. L. Carter, 1997; Dreger & Reimers, 2005; Fan & Savedoff, 2014; Hall & Jones, 2007; Ke et al., 2011; Murthy & Okunade, 2016; Roberts, 1999). Investment in medical technology and the use of advanced medical equipment can improve quality of life and longevity. On the other hand, life expectancy may reflect the pattern of prevalent diseases in a country. In countries where there is high prevalence of infectious diseases (like tuberculosis, malaria and HIV), life expectancy at birth is often low. Low average life expectancy can, in turn, drive the need to demand more healthcare services to improve the current stock of health, thus increases spending on health. Ke et al. (2011) also noted that life expectancy can determine the size of external aid a country receives for disease programmes. For the purposes of this study, life expectancy is therefore expected to increase health expenditure in Africa.

Infant Mortality Rate

Like life expectancy, infant mortality is another proxy for quality of life and medical technological advancement (Dreger & Reimers, 2005). In Africa, rising infant mortality rate is expected to increase investment in health technologies and development programmes to

[39] Other measures of medical technological progress that have been considered for empirical analysis are: surgical procedure and number of specific medical equipment (Baker & Wheeler, 1998; T. P. Weil, 1995); infant mortality (Dreger & Reimers, 2005); time index (Gerdtham & Löthgren, 2000); time-specific intercepts (Di Matteo, 2005); and health research and development (R&D) expenditure (Murthy & Okunade, 2016).

achieve one of the health related Millennium Development Goals (MDGs)[40] and this might increase demand for healthcare services.

Population Structure

Population structure is another factor often used in the literature to explain changes in health care expenditure. The commonly considered age groups among the few documented African studies are population under 15 (e.g. Gbesemete & Gerdtham, 1992) and over 65 years of age (e.g. V. N. R. Murthy & A. A. Okunade, 2009). Both of these metrics have a significant positive relationship with healthcare expenditure (e.g. Di Matteo, 2005; Hitiris & Posnett, 1992; H. N. Khan et al., 2016; Lv & Xu, 2016; Moscone & Tosetti, 2010; Murthy & Okunade, 2016; O'Connell, 1996; Sen, 2005).

Official Development Assistance

Most African countries are recipients of significant foreign aid and Official Development Assistance - often designated for addressing health-related issues and creating health programmes. In Africa, ODA can either account for a large share of the government health expenditure or may replace it totally. However, the weak governance and institutional framework in Africa, and the possibility of foreign aid being diverted from public investment to non-health consumption, make it difficult to account for the impact and effectiveness of ODA on health (Carlsson, Somolekae, & Van de Walle, 1997; H. A. Khan, 1998; Okunade, 2005). Ceteris paribus, net real ODA is expected to significantly increase health expenditure since it is the real source of inflow for health development in Africa. At the same time, its effect on out-of-pocket expenditure may be negative or insignificant because it is expected to reduce the financial burden on households.

[40] Now called Sustainable Development Goals (http://www.undp.org/content/undp/en/home/sustainable-development-goals.html)

The ODA data used in this study comprises external finance for health and non-health programmes and projects. Due to undocumented utilization of ODA funds and unavailability of data for health-related ODA, it is difficult to precisely determine the effect of ODA in driving health spending for Africa countries.

Government Fiscal Capacity

Government fiscal capacity is the ratio of total government expenditure to GDP. It is an indicator of available resources at the disposal of the government. It is a metric often used to determine if a country's health system development is a priority in a particular fiscal year depending on its relative share compared to other social and economic sectors. At the output level, public budget for health expenditure is expected to increase as more resources become available (Ke et al., 2011). There is a possibility of unconditioned ODA to increase the size of government total expenditure, then affect fiscal capacity for health. Like ODA, total government expenditure as a share of GDP is expected to reduce out-of-pocket expenditure. To the best of my knowledge, there is no study for African countries that models government fiscal capacity to explain changes in all forms of health care expenditure. Another closely related metric found in studies (Di Matteo, 2003, 2005) for developed countries is government revenue as a share of income.

5.6 Data and Methods

The methodology for this study consists of five key sections: data description and sources; estimation strategy; pre-estimation diagnostic tests; post-estimation tests; and robustness checks.

5.6.1 Data Description and Sources

A description of the variables required to conduct the baseline analyses and robustness checks is provided in Table 5.4.

Table 5.4: Data Description and Sources

Notation	*Description*	*Source*
THE	Real Total Health expenditure per capita;	WDI (2017)
GHE	Real Public Health expenditure per capita;	WDI (2017)
OPE	Real Out-of-pocket health expenditure per capita;	WDI (2017)
GDP	Real GDP Per Capita	WDI (2017)
LEX	Life expectancy at birth, total (years);	WDI (2017)
INM	Infant mortality (per 1,000 live births)	WDI (2017)
P65	Population aged 65 and above (% of total population).	WDI (2017)
P15	Population aged 0-14 (% of total population);	WDI (2017)
GFC	Total Government Expenditure as a share of GDP	WDI (2017)
ODA	Real Net Official Development Assistance (ODA) and Official Aid Received Per Capita;	WDI (2017)

NOTE: WDI = World Development Indicators

5.6.2 Estimation Strategy and Baseline Model Specification

It is a standard approach in econometrics literature to estimate specifications like Equation (5.1) using a fixed effect or random effect method (Baltagi, 2013; Greene, 2011; Wooldridge, 2010) if the data are pooled and the strict classical assumptions are maintained. However, severe biases can arise for pooled observations by assuming homogenous slope coefficients. Such an assumption is highly restrictive in a panel with heterogeneous units/individuals (Ando & Bai, 2015; Baltagi & Pesaran, 2007; Lin & Ng, 2012; Pesaran et al., 1999; Pesaran & Smith, 1995).

Evidence from Monte Carlo experiments by Robertson and Symons (1992) argues against homogeneous estimates through data pooling. Likewise, Pedroni (2007) shows that accounting for heterogeneity is essential to explain differences in observed patterns across countries. In Baltagi and Moscone (2010) similarly acknowledge that in the presence of heterogeneous intercepts across groups, the validity of hypotheses of homogenous income elasticities and trend (as a proxy for technological advancement) are highly questionable. Also, Zerihun, Cunado, and Gupta (2017) reported evidence of asymmetric behaviour in modelling healthcare expenditure and income. That is, each country's unique characteristics are reflected in the variables and a standard linear model is inadequate. To incorporate heterogeneity into my analysis of the health spending-income nexus for African countries, an extended version of Equation (5.1) is specified as follows:

$$HCE_{it} = \beta'_{m,i} X_{m,it} + u_{it} \tag{5.2}$$

$$\beta_{m,i} = \beta_m + \eta_{m,i} \tag{5.3}$$

$$u_{it} = \mu_i + \lambda'_i f_t + \omega_{it} \tag{5.4}$$

$$\lambda_i = \lambda + \zeta_i \tag{5.5}$$

$$x_{m,it} = \pi_{m,i} + \delta'_{m,i} g_{m,t} + \rho_{1m,i} f_{1m,t} + \ldots + \rho_{nm,i} f_{nm,t} + v_{m,it} \tag{5.6}$$

$$f_t = \vartheta' f_{t-1} + \upsilon_t \tag{5.7}$$

$$g_t = \kappa' g_{t-1} + \upsilon_t \tag{5.8}$$

where $i = 1, 2, \ldots, N$; $t = 1, 2, \ldots, T$; $m = 1, 2, \ldots, k$; and $f_{.mt} \subset f_t$; $\beta_{m,i}$ is a k x 1 vector of slope coefficients of k number of explanatory variables that vary across countries (i.e. heterogeneous); $\beta_{m,i}$ follows a random coefficients process as defined in Equation (5.3); β_m is the common slope vector and $\eta_{m,i}$ is a group-specific random term; u_{it} is the composite error term in the multifactor residual model (5.4) employed to model cross-sectional dependence[41]; μ_i is the unobservable group-specific fixed effects; f_t is the time-variant

[41] The multifactor error model can also be used to study common macroeconomic shocks across groups such as the global financial crisis or oil price shocks. Also, it provides a framework that allows for heterogeneous responses to "common shocks" through a heterogeneous factor loading, λ_i (Baltagi, 2013, p. 287; Moon & Perron, 2004) and accommodates a complex covariance structure (Hsiao & Pesaran, 2004).

unobserved common factor with heterogeneous factor loading, λ_i , and it can follow a non-stationary process as expressed in Equation (5.7). The factor loading, λ_i , follows a random coefficient process as shown in Equation (5.5); ω_{it} is the idiosyncratic error assumed to be independently distributed across groups (i), f_t , and x_{it} with zero mean and constant variance.

In Equation (5.6), $x_{m,it}$ are the k observable explanatory variables: GDP_{it} , LEX_{it} , INM_{it} , $P65_{it}$, $P15_{it}$, ODA_{it} and GFC_{it} as specified in Equation (5.1). It is expressed as a linear function of: (i) a country specific fixed effect, $\pi_{m,i}$; (ii) time-variant unobserved common factors $g_{m,t}$ and $f_{m,t}$ with respective heterogeneous factor loadings of $\delta_{m,i}$ and $\rho_{m,i}$ for k explanatory variables; and (iii) an idiosyncratic error term v_{it} assumed to be independent and identically distributed. The common unobservable factors f_t and g_t are potentially non-stationary ($\vartheta = 1, \kappa = 1$) as shown in Equations (5.7) and (5.8).

The factors model (5.4) is adopted to account for unobservable risk factors associated with health spending (Baltagi & Moscone, 2010) such as geographic patterns[42] of diseases induced by environmental factors; diet; lifestyle (Haining, 2003); border proximity; intra-continental migration; unobservable heterogeneous effects of fragility, conflicts and civil wars on health care spending; inter-dependent health policy programmes; and health reforms. These factors can induce unobservable cross-sectional correlation in the empirical model set-up[43] (Equations 5.2 – 5.8). This framework has been recently used in a number of high profile

[42] The differential geographic concentration of diseases (such as malaria, polio, tuberculosis and HIV/AIDS that are common in Africa) is a plausible contributor to the variation in health expenditure across countries and a determinant of foreign aid size to be received by the African countries.
[43] It is essential to note that the highlighted factors are common to these groups of countries but not identical across countries.

studies (in Baltagi & Moscone, 2010; Bond & Eberhardt, 2013a; Eberhardt, Helmers, & Strauss, 2013; Eberhardt & Presbitero, 2015; Eberhardt & Teal, 2012, 2013a, 2013b, 2014; Kapetanios et al., 2011; Pesaran, 2006).

It is clear from the empirical model set-up that the unobservable common factors f_t affect the composite error term u_{it} (Equation (5.4)) and the k vector of explanatory variables $x_{m,it}$ (Equation (5.6)). This yields two main effects: (i) the unobservable common shocks f_t affect health care expenditure (HCE_{it}) through the multifactor error model (Equation (5.4)) and a set of exogenous variables (Equation (5.6)); and (ii) it induces endogeneity through correlation between $x_{m,it}$ and u_{it}. The latter makes it difficult to identify the slope coefficients $\beta_{m,i}$ from the heterogeneous factor loadings λ_i and $\rho_{m,i}$ (Eberhardt & Teal, 2012; Kapetanios et al., 2011). Comparatively, the empirical framework adopted here is different from the model set-up of Equation (5.1) in three ways: (i) heterogeneous effects of the regressors and unobserved common factors on health care expenditure; (ii) potential non-stationarity of the observables (HCE_{it} and $X_{m,it}$) and unobservables (f_t and g_t); and (iii) endogeneity[44] of the explanatory variables induced by the common factors. It is conventional in the literature to estimate the extended empirical model framework with respect to the first feature alone. This can be achieved using Swamy (1970) Random Coefficients Model estimation method to obtain a weighted average of the panel-specific OLS estimates. Also, the Pesaran and Smith (1995) Mean Group estimator can be applied by estimating country specific OLS and taking the simple average of all the countries' estimates. Unlike the Swamy's RCM method, the mean group estimator is super consistent if the regressors are I(1) (Pesaran & Smith, 1995). The MG

[44] Other sources of endogeneity are identified and described under the introductory section of this chapter..

estimator has been found to perform poorly under the considered set-up as demonstrated in Chapter 4 using Monte Carlo simulation.

However, the above two estimators (RCM and MG) ignore cross-sectional dependence and a multifactor error structure. To implement the set-up empirically with all its potential features ([i], [ii] and [iii]), the estimators capable of accounting for the issues are: the Common Correlated Effects Mean Group estimator by Pesaran (2006) and the Augmented Mean Group estimator by Eberhardt and Teal (2012) and Bond and Eberhardt (2009). In the set-ups considered in Chapter 4, CCEMG was found to perform well and AMG was generally less effective in addressing endogeneity. In this chapter, CCEMG is used for estimating the baseline model, while AMG is used for robustness checks.

The CCEMG estimation procedure follows two steps. The first step involves estimating country-specific regressions with additional covariates - $\overline{LRHEPC_t}$ and $\bar{x}_{m,t}$ - as proxies for the unobserved common factors f_t. The second step consists of obtaining the simple average of the individual specific OLS estimates of the slope coefficients as $\hat{\beta}_{m,CCEMG} = N^{-1}\sum_i \hat{\beta}_{m,i}$ (for more details, see Pesaran, 2006).

The AMG estimator follows a three-step approach. The first step requires estimation of the pooled OLS regression in first difference augmented with T-1 year dummies. The estimated coefficients ($\hat{\mu}_t^{\bullet}$, known as “common dynamic process”) on the differenced year dummies are obtained. They represent the estimated cross-sectional averages of the evolution of unobservables over time. Second, N group-specific regressions of Equation (5.2) augmented with $\hat{\mu}_t^{\bullet}$ and heterogeneous linear trends are estimated. Finally, an average of the estimated coefficients across groups is obtained, $\hat{\beta}_{m,AMG} = N^{-1}\sum_i \hat{\beta}_{m,i}$ (for an extensive discussion, see Bond & Eberhardt, 2013a). Both CCEMG and AMG follow the MG approach in determining the average slope coefficient of individual group estimates. As demonstrated in Chapter 4, the two estimators are desirable for large panels in the presence of parameter heterogeneity, serial and cross-sectional correlation.

A test of slope homogeneity was performed as a robustness check using the test statistic suggested by Swamy (1970). The test examines the difference between group-specific OLS estimate of the slope coefficient, while ignoring the panel data structure and the matrix-weighted average of the group-specific OLS estimates (see Johnston and DiNardo (1997) for details).

On the basis of the described estimation framework adopted for this study, model (5.1) is re-specified to account for heterogeneous slopes and linear time trends as follows:

$$\begin{aligned} HCE_{it} &= \alpha + \beta_{i,1} GDP_{it} + \beta_{i,2} LEX_{it} + \beta_{i,3} INM_{it} + \beta_4 P65_{it} \\ &+ \beta_{i,5} P15_{it} + \beta_{i,6} ODA_{it} + \beta_{i,7} GFC_{it} + \beta_{i,8} trend + \mu_i + \omega_{it} \end{aligned} \quad (5.9)$$

The linear time trends ($trend$) incorporated in model (5.9) is used as a proxy for medical technological progress (A. G. Blomqvist & R. A. L. Carter, 1997; Di Matteo, 2005; Gerdtham & Löthgren, 2000; Okunade & Murthy, 2002; Roberts, 1999), and changes in medical practices and innovations over time (Ke et al., 2011). To the best of my knowledge, no panel study for African countries has ever made an attempt to model medical technical progress for explaining the determinants of health expenditure. Also, despite the plethora of empirical research in this area for developed countries, as far as I know, no existing OECD studies (e.g. Baltagi & Moscone, 2010; De Mello-Sampayo & De Sousa-Vale, 2014; Moscone & Tosetti, 2010) use the heterogeneous trends framework to examine the relationship between health expenditure and income. The identified gaps (for African and OECD studies) are filled in this study by estimating the baseline model (5.9) with heterogeneous ($\beta_{i,8}$) linear time trends $(trend)$.

For Equation (5.9), $\beta_{i,1}$ is the country-specific income elasticity of healthcare expenditure; and $\beta_{i,2-7}$ are the heterogeneous parameters for the set of explanatory variables as previously defined. All other parameters follow the heterogeneous model set-up framework (5.2 – 5.8) described above.

5.6.3 Pre-Estimation Diagnostic Tests

5.6.3.1 Testing for Cross-Sectional Dependence

As argued throughout this thesis, the presence of cross-sectional correlation in residuals has severe implications for standard panel data estimators' (such as POLS, RE, and FE) efficiency and consistency attributes. This study therefore tests for cross-sectional correlation of variables in the empirical model (5.2). Baltagi and Moscone (2010, p. 807) emphasise the need to do so using Pesaran's (2004) procedure. Due to potential inconsistency in Pesaran's (2004) CD test for large N, another alternative is to employ the bias-adjusted variant of Breusch and Pagan (1980) Lagrange Multiplier (BALM) test statistic developed by Pesaran, Ullah, and Yamagata (2008).

The BALM test has desirable finite sample properties, successfully controls for size and maintains appropriate power when the regressors are exogenous and errors are normal. However, the BALM test statistic is only valid for static models unlike Pesaran's (2004) CD test statistic that extends to dynamic models. Also, the BALM test requires a strongly balanced panel and can only be used as a post-estimation test of error cross-sectional independence. Pesaran's (2004) CD test is valid for pre and post estimation tests. In this study, the Pesaran's (2004) CD test is used for pre-estimation diagnostic checks and to justify the need to use the recently developed panel data estimators.

5.6.3.2 Testing for Panel Unit Root

The Fisher's combined p-values test proposed by Maddala and Wu (1999) is a heterogeneous Panel Unit Root Test and a first generation test. The test combines p-values from individual specific unit root models to test for non-stationarity in panel data. Unlike the Im et al. (2003) (henceforth, IPS) PURT, Fisher's test uses different lag lengths for individual Augmented Dickey-Fuller regressions and does not require a balanced panel. Maddala and Wu (1999) improve the power of the Fisher's test with bootstrap-based critical values (Baltagi, 2013, p. 283). This combined test is found to be superior to the IPS test and Levin, Lin, and Chu (2002) (henceforth, LLC) PURT (Maddala, Wu, & Liu, 2000), and performs better when N is small (Choi, 2001). For the purpose of this chapter, the Fisher's PURT is the only first generation test considered to examine the stationarity of the incorporated series in Equation (5.1).[45]

The restrictive assumption of cross-sectional independence of individual time series underlying first generation PURTs (see Baltagi and Kao (2000) for an extensive review) limits their size and power performance. Therefore, to account for cross-sectional dependence, "second generation" PURTs (with different residual factor structures) have been developed (Breitung & Pesaran, 2008). Of interest to this study is the Pesaran (2007) cross-sectionally augmented Im, Pesaran and Shin (2003) (henceforth, CIPS) PURT. The test is based on the augmented individual cross-section ADF (CADF) regressions of y_{it} with cross-section averages of (lagged levels and first difference) $\bar{y}_{t-1} = N^{-1}\sum_{i=1}^{N} y_{i,t-1}$ and $\Delta\bar{y}_t$ (to account for residual cross-sectional dependence) and lagged first difference of the individual series, $\Delta y_{i,t-s}$, $\Delta\bar{y}_{t-s}$, for $s = 1, 2, \ldots$, to deal with likely residuals' serial correlation (Pesaran, 2007; Pesaran, Smith, & Yamagata, 2013). The CIPS test statistic is the simple average of the individual CADF statistics; i.e., $CIPS = N^{-1}\sum_{i=1}^{N} CADF_i$. Using Monte Carlo experiments, Pesaran (2007) shows that the CIPS test has desirable small sample properties in the presence of a single

[45] Other first generation PURTs (such as Levin et al. (2002), Breitung (2001) and Hadri (2000)) require a strongly balanced panel that is not available for this study.

unobserved common factor and is also valid for panels with large N and T. Gengenbach, Palm, and Urbain (2009) demonstrate that the test can exhibit size distortion if the number of common factors exceeds one. An extension of the CIPS test in a case of multifactor error structure (CIPSM) is provided in Pesaran et al. (2013). The CIPS test is robust to cross-sectional dependence, individual specific residual serial correlation and incidental deterministic intercepts and trends (Pesaran, 2007).

In this study, I consider the truncated version of the CIPS test (CIPS*) where the group-specific CADF statistics are conveniently truncated (CADF*) to avoid nuisance parameters. The adopted PURTs in this study have the null hypothesis that all individual series in the panel have a unit root against the alternative that allows for a fraction of the individual series to contain unit roots (Baltagi, 2013).

5.6.4 Post-Estimation Residual Based Tests

5.6.4.1 Inspecting Size of Cross-Sectional Dependence

The cross-sectional correlation of residuals generated from estimating Equation (5.9) is examined using the Pesaran (2004) CD test. This is to inspect the absolute size of the cross-sectional coefficient of the residuals and justify the robustness of adopted panel data estimators (CCEMG and AMG). The estimators are not designed to eliminate cross-sectional correlation entirely but to reduce its size in order to derive consistent and efficient estimates (De Hoyos & Sarafidis, 2006). For consistency purpose, I made an attempt to implement the bias-adjusted variant of Breusch and Pagan (1980) Lagrange Multiplier test statistic proposed by Pesaran et al. (2008) but the available dataset is not sufficiently balanced to perform the test.

5.6.4.2 Testing for Cointegration

Cointegration between health spending and income for African countries is determined using a residual-based method that accounts for cross-sectional dependence, heterogeneity, and potential serial correlation. If Pesaran's (2007) CIPS test statistic is significant, it indicates that the residual series is stationary and the null hypothesis of no cointegration is rejected[46]. For the purpose of this study, the CIPS test approach is used despite unavailability of testing critical values as a residual based cointegration technique compared to other Error Correction Model (ECM) based tests. This includes Westerlund (2007)[47] test that does not implicitly account for cross-sectional dependence and assumes a common factor structure for cross-sectional dependence. For consistency checks, I made an attempt to implement the Gengenbach, Urbain, and Westerlund (2009) ECM approach and the Pesaran et al. (2013) CIPSM residual based cointegration techniques but the available dataset is not sufficiently balanced to perform the tests. Then, I applied a coinetgration test developed by Pedroni (1999, 2004) that comprises of four pooled and three group-mean statistics. The null hypothesis of all the seven tests is "no cointegration".[48]

5.6.5 Robustness and Consistency Checks of Estimators and Tests

The robustness and consistency checks used in this study are summarized in Table 5.5.

[46] The appropriate critical values for CIPS procedures test in testing for cointegration is not available as at the time of this research. My approach here is ad hoc and might be less robust but other earlier empirical studies (Baltagi & Moscone, 2010; Baltagi et al., 2012; Hashiguchi & Hamori, 2012) have used CIPS as a cointegration technique.
[47] The implementation of the Westerlund's (2007) cointegration technique requires strongly balanced panel without gaps and total number of variables not more than 6. Both of which a not available for this study.
[48]The Pedroni (1999, 2004) tests can only be implemented whwn the number of regressors in the model is not more than 7 (Neal, 2014).

Table 5.5: Methodological Summary for Baseline Analysis and Analytical Checks

Methods	***Baseline Analysis***	***Robustness Checks***	***Consistency Checks***
Estimator	CCEMG	Homogenous: 2WFE & POLS	Heterogeneous: AMG
CD Test	PCD test		
PURT	Fisher's combined MW test and CIPS test		
Panel Cointegration	Residual based: CIPS test		Pooled and Group-mean panel cointegration tests (Pedroni, 1999, 2004)

NOTE: 2WFE = Two-Way Fixed Effect; PCD = Pesaran’s (2014) Cross-sectional Dependence; MW = Maddala & Wu (1999).

5.6.7 Robustness Checks of the Model Specification and Sub-Sample Analysis

As a robustness check, I have modified the baseline model specification in three ways: (i) baseline model re-estimated without a linear time trend, (ii) samples reclassified based on trending exchange rate fluctuations, and (iii) data sub-samples. The objective of the checks is to examine the extent to which the estimated income elasticity of healthcare expenditure in African countries is robust to: (i) changes in model specification, (ii) exclusion of countries with high exchange rate volatility driven by PPP adjustment, and (iii) decomposition of the pooled dataset into sub-samples. The income elasticity coefficient from each category is compared with the baseline elasticity estimate from Equation (5.9). Also, a visual inspection of the differences in the estimates is provided by plotting the average income elasticity coefficient and the upper and lower confidence intervals for the estimated coefficient. The floating bars plot is used to indicate the extent to which the income elasticity estimates from each category differ from the baseline average elasticity coefficient.

Model Re-Specification

The baseline empirical model (5.9) is re-specified without a linear heterogeneous trend as:

$$\begin{aligned} HCE_{it} &= \alpha + \beta_{i,1} GDP_{it} + \beta_{i,2} LEX_{it} + \beta_{i,3} INM_{it} + \beta_4 P65_{it} \\ &\quad + \beta_{i,5} P15_{it} + \beta_{i,6} ODA_{it} + \beta_{i,7} GFC_{it} + \mu_i + \omega_{it} \end{aligned} \tag{5.10}$$

Model (5.10) is estimated using CCEMG to determine if the baseline income elasticity coefficient is driven by inclusion of the heterogeneous linear time trends. The size and significance of the elasticity coefficient are compared with the estimate from (5.9).

Country Split by Exchange Rate Variation

All the variables incorporated in model (5.9) excluding the demographic indicators (LEX, INM, P65 and P15) are measured in real level using purchasing power parity (PPP) conversion. I investigate whether the elasticity estimates are being driven by PPP adjustment considering the level of exchange rate fluctuations across African countries vis-à-vis the U.S. dollar. The plots (Figures 5.3 - 5.6) of the consumption version of the PPP and the log of real total health expenditure per capita are used to select countries for exclusion from the dataset.

Countries with high exchange rate variation relative to the total health expenditure per capita include: Burundi, Congo Dem. Rep., Guinea, Madagascar, Sierra Leone, Tanzania, and Uganda. These seven countries are categorised as an "unstable sub-sample" for the purposes of this robustness check. The elasticity estimates from the stable and unstable sub-samples are compared with the elasticity coefficient from the baseline model (5.9).

To the best of my knowledge, the country split approach for testing the robustness of the baseline model to exchange rate variation in Africa is novel. For OECD countries, Narayan et al. (2010) used a different approach by comparing the elasticity estimates between variables adjusted by the GDP deflator and those adjusted using a country-specific healthcare price

Figure 5.3: Trend of Purchasing Power Parity (PPP) for selected African Countries (I)

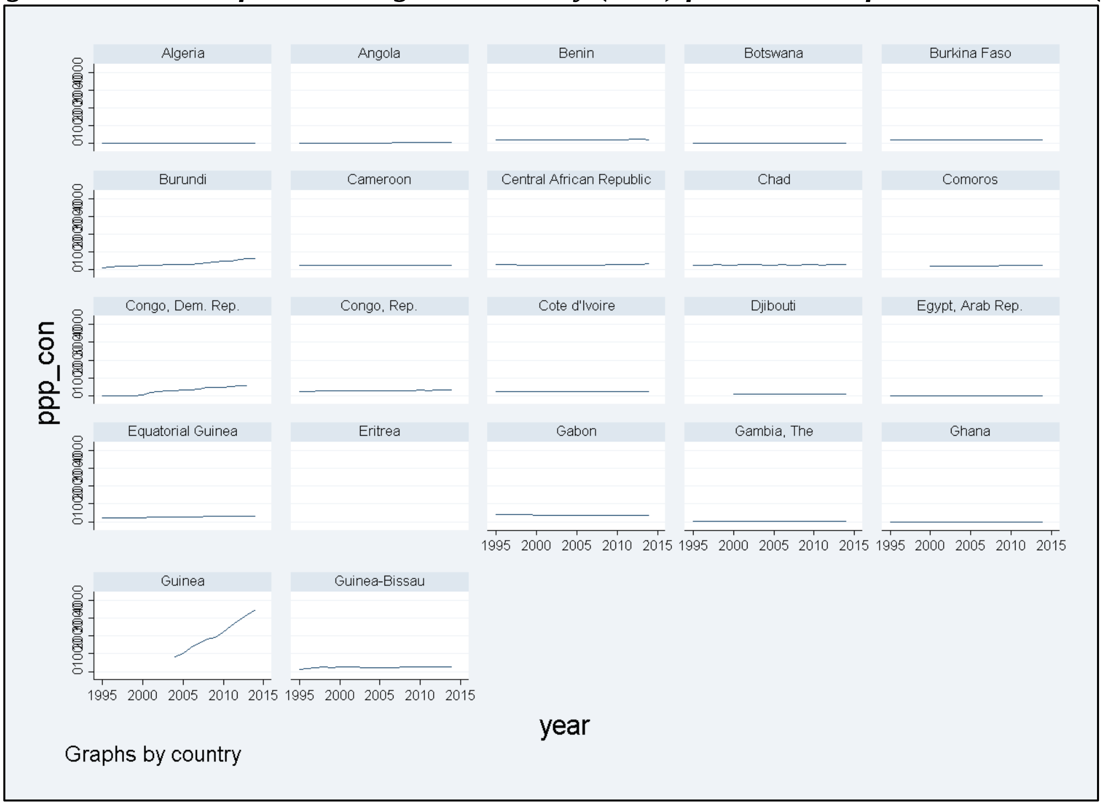


Figure 5.4: Trend of Purchasing Power Parity (PPP) for selected African Countries (II)

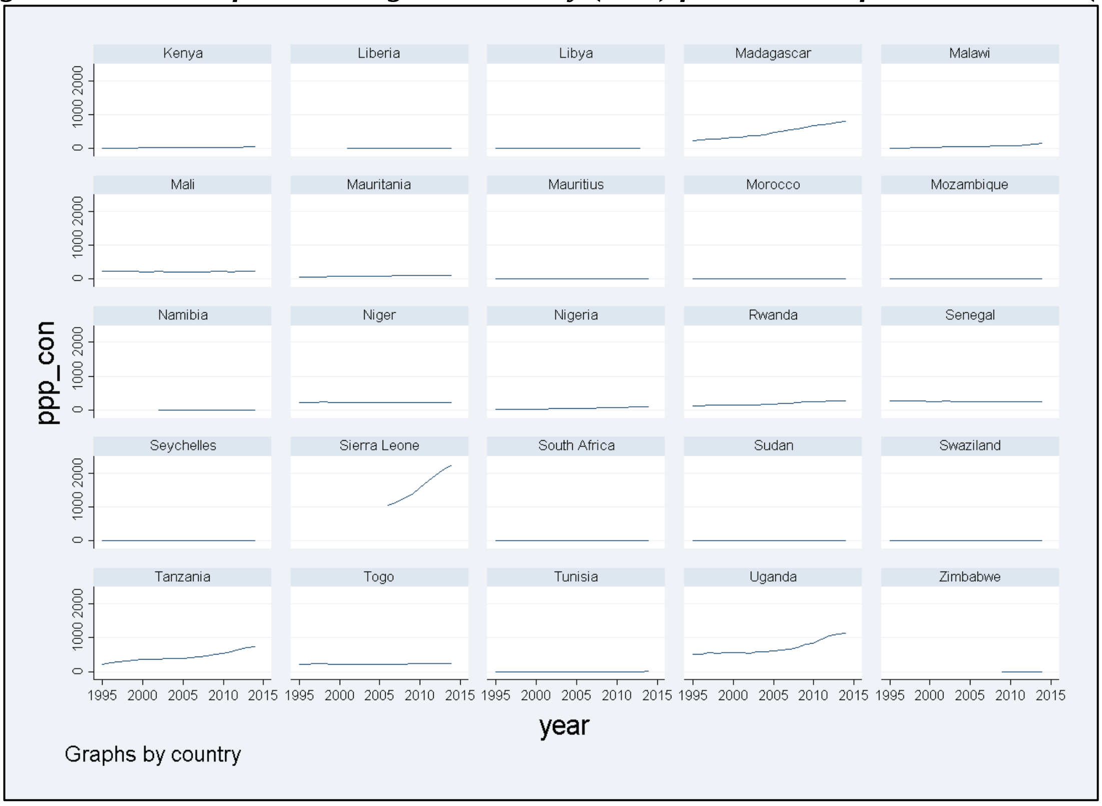


Figure 5.5: Trend of Real Total Health Expenditure for selected African Countries (I)

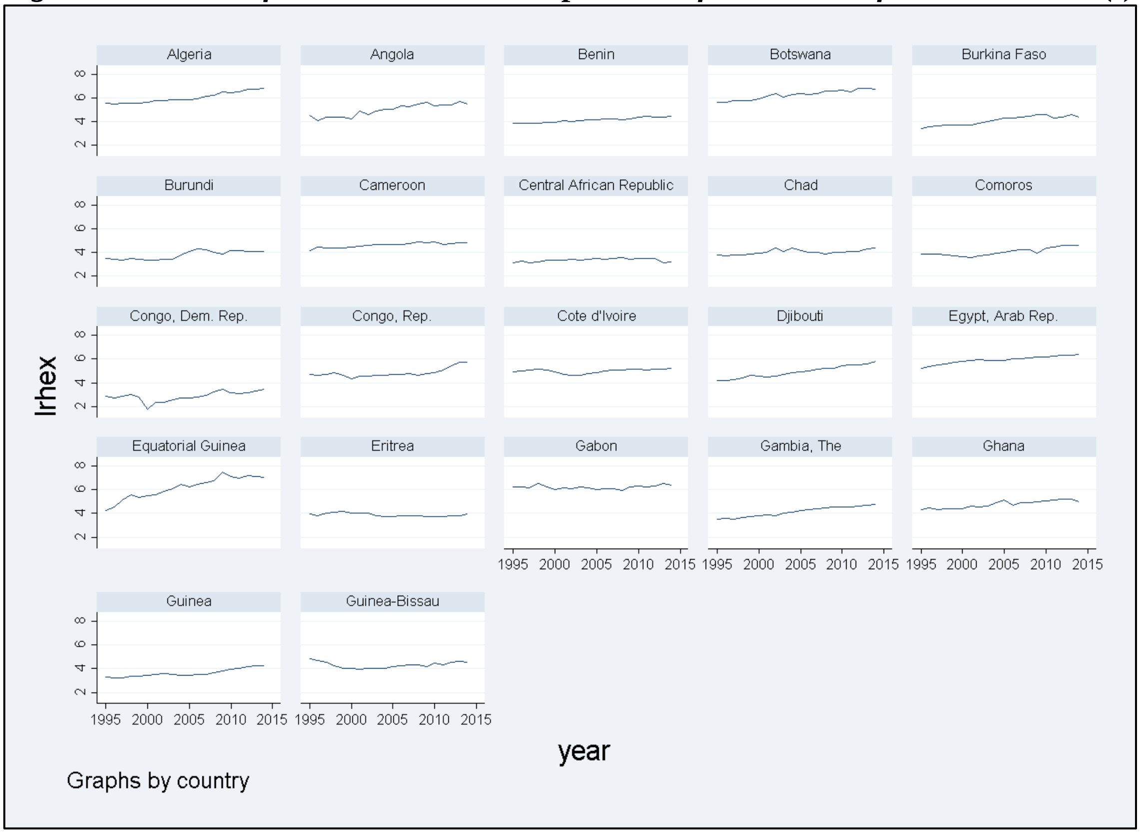
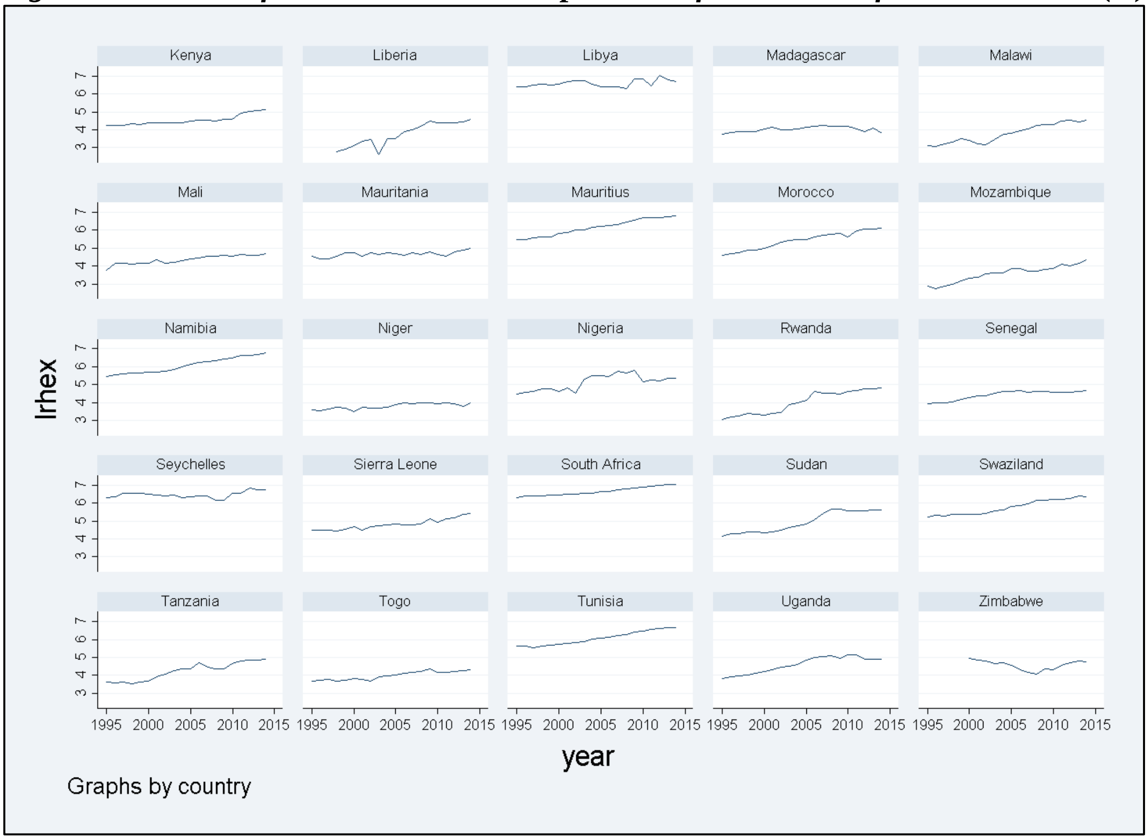


Figure 5.6: Trend of Real Total Health Expenditure for selected African Countries (II)



index. They found that the use of the GDP deflator produces biased estimates and can lead to wrong policy inference in determining whether health is a necessity or luxury good.

Geo-Political Sub-Sample Analysis

The full sample of countries used in the baseline analysis consists of 47 out of 54 African states (Table 5.6). Seven countries had to be excluded due to lack of data. These countries are: Cabo Verde, Ethiopia, Lesotho, Sao Tome and Principe, Somalia, South Sudan and Zambia (highlighted in yellow in Table 5.6). The period from 1995 to 2014 is chosen for this study due to data availability across countries; still, the dataset is not strongly balanced[49].

In further robustness checks, the full sample is split into sub-samples based on the World Bank (2017) regional classification and income groups and the Peace (2016)fragile state

[49] The unbalanced nature of the panel dataset limits the choice of robustness and diagnostic tests performed in this study.

index[50] (Table 5.6). The first classification involves grouping the countries into geographical regions with similar economic and social characteristics. It is conventional to categorise African countries into Sub-Saharan Africa (SSA; 41 countries) and North Africa (6 countries). SSA can be further split into the West (17 countries), East (11 countries), South (8 countries) and Central (5 countries) sub-regions. The SSA and North Africa datasets are used to individually estimate Equation (5.9). Then, the income elasticity coefficients are compared with the baseline estimate.

In a second classification, Equation (5.9) is estimated for four different African income groups[51]: lower middle income (13 countries), upper middle income (9 countries), low income (24 countries), and high income (1 country). Only Seychelles is in the high income group and a time series OLS estimator is used instead of CCEMG. Income elasticity estimates from each of the income groups are compared with the baseline estimate.

Table 5.6: Classification of African Countries by Region, Income and Fragility Status

No.	***Country***	***Region***	***Sub-Region***	***Income Group***	***Fragility Status***	***FSI (2016)***
1	***Algeria***	NA	NA	UMI	NFR	78.3
2	***Angola***	SSA	SA	UMI	FRA	90.5
3	***Benin***	SSA	WA	LIN	NFR	78.9
4	***Botswana***	SSA	SA	UMI	NFR	63.5
5	***Burkina Faso***	SSA	WA	LIN	FRA	89.4
6	***Burundi***	SSA	EA	LIN	FRA	100.7
7	***Cabo Verde***	SSA	WA	LMI	FRA	71.5
8	***Cameroon***	SSA	WA	LMI	NFR	97.8

50 Details and ranking of the FSI 2016 can be retrieved from: http://fsi.fundforpeace.org/rankings-2016
51 See Figure 5.1 for Africa’s income distribution map.

No.	Country	Region	Sub-Region	Income Group	Fragility Status	FSI (2016)
9	*Central African Republic*	SSA	CA	LIN	FRA	112.1
10	*Chad*	SSA	WA	LIN	FRA	110.1
11	*Comoros*	SSA	EA	LIN	NFR	83.8
12	*Congo, Dem. Rep.*	SSA	CA	LIN	FRA	110
13	*Congo, Rep.*	SSA	CA	LMI	FRA	92.2
14	*Côte d'Ivoire*	SSA	WA	LMI	FRA	97.9
15	*Djibouti*	NA	NA	LMI	FRA	89.7
16	*Egypt, Arab Rep.*	NA	NA	LMI	FRA	90.2
17	*Equatorial Guinea*	SSA	CA	UMI	NFR	85.2
18	*Eritrea*	SSA	EA	LIN	FRA	98.6
19	*Ethiopia*	SSA	EA	LIN	FRA	97.2
20	*Gabon*	SSA	CA	UMI	NFR	72
21	*Gambia, The*	SSA	WA	LIN	FRA	86.8
22	*Ghana*	SSA	WA	LMI	NFR	71.2
23	*Guinea*	SSA	WA	LIN	FRA	103.8
24	*Guinea-Bissau*	SSA	WA	LIN	FRA	99.8
25	*Kenya*	SSA	EA	LMI	FRA	98.3
26	*Lesotho*	SSA	SA	LMI	NFR	80.9
27	*Liberia*	SSA	WA	LIN	FRA	95.5
28	*Libya*	NA	NA	UMI	FRA	96.4

No.	Country	Region	Sub-Region	Income Group	Fragility Status	FSI (2016)
29	*Madagascar*	SSA	EA	LIN	NFR	84.2
30	*Malawi*	SSA	SA	LIN	FRA	87.6
31	*Mali*	SSA	WA	LIN	FRA	95.2
32	*Mauritania*	SSA	WA	LMI	FRA	95.4
33	*Mauritius*	SSA	EA	UMI	NFR	43.2
34	*Morocco*	NA	NA	LMI	NFR	74.2
35	*Mozambique*	SSA	SA	LIN	FRA	87.8
36	*Namibia*	SSA	SA	UMI	NFR	71.1
37	*Niger*	SSA	WA	LIN	FRA	98.4
38	*Nigeria*	SSA	WA	LMI	FRA	103.5
39	*Rwanda*	SSA	EA	LIN	FRA	91.3
40	*São Tomé and Principe*	SSA	CA	LMI	NFR	72.9
41	*Senegal*	SSA	WA	LIN	NFR	83.6
42	*Seychelles*	SSA	EA	HIN	NFR	60.2
43	*Sierra Leone*	SSA	WA	LIN	FRA	91
44	*Somalia*	SSA	EA	LIN	FRA	114
45	*South Africa*	SSA	SA	UMI	NFR	69.9
46	*South Sudan*	SSA	EA	LIN	FRA	113.8
47	*Sudan*	SSA	EA	LMI	FRA	111.5
48	*Swaziland*	SSA	SA	LMI	FRA	87.6

No.	Country	Region	Sub-Region	Income Group	Fragility Status	FSI (2016)
49	***Tanzania***	SSA	EA	LIN	NFR	81.8
50	***Togo***	SSA	WA	LIN	NFR	85.8
51	***Tunisia***	NA	NA	LMI	NFR	74.6
52	***Uganda***	SSA	EA	LIN	FRA	97.7
53	***Zambia***	SSA	SA	LMI	FRA	86.3
54	***Zimbabwe***	SSA	SA	LIN	FRA	100.5

NOTE: SSA = Sub-Saharan Africa; NA = North Africa; CA = Central Africa; EA = East Africa; WA = West Africa; SA = Southern Africa; UMI = Upper middle income; LIN = Low income; LMI = Lower middle income; HIN = High income; FRA = Fragile; NFR = Non-Fragile

Lastly, the countries are categorised into fragile and non-fragile African states using the 2016 fragile state index (FSI). The FSI is a composite of 12 indices: demographic pressures; refugees and Internally Displaced People (IDPs); group grievance; human flight; uneven development; poverty and economic decline; legitimacy of the state; public services; human rights; security apparatus; factionalized elites; and external intervention. Each of the indices has a 10-point score ranging from 1 (very good) to 10 (very poor). The FSI has a total of 120 points. Countries with FSI of 86 and above are classified as fragile (34 countries) and those with FSI less than 86 are grouped as non-fragile (20 countries). The FSI sub-samples are used to estimate Equation (5.9) and the estimated income elasticity coefficients are compared with the baseline elasticity estimate.

A summary of all robustness checks considered in this study is presented in Table 5.7.

Table 5.7: Summary of Robustness Checks

No.	***Type of Robustness Check***	***Model***	***Dataset***	***Method***	***Parameter***
1	***Baseline Analysis***	Eq. (5.9)	Full sample	CCEMG	$\overline{\beta}_{i,1}$
2	***Model Re-Specification:***				
	Baseline model without trends	Eq. (5.10)	Full sample	CCEMG	$\overline{\beta}_{i,1}^{TR}$
3	***Country Split by Exchange Rate Variation:***				
	Stable exchange rate fluctuation	Eq. (5.9)	Stable sample	CCEMG	$\overline{\beta}_{i,1}^{ST}$
	Unstable exchange rate fluctuation	Eq. (5.9)	Unstable sample	CCEMG	$\overline{\beta}_{i,1}^{US}$
4	***Estimation Methods:***				
	Pooled type estimators	Eq. (5.9)	Full sample	POLS & 2WFE	$\overline{\beta}_{i,1}^{PO}$
	Mean group type estimator	Eq. (5.9)	Full sample	AMG	$\overline{\beta}_{i,1}^{MG}$
5	***Data Decomposition:***				
	[A] Income group:				
	Lower middle income	Eq. (5.9)	LMI dataset	CCEMG	$\overline{\beta}_{i,1}^{LM}$
	Upper middle income	Eq. (5.9)	UMI dataset	CCEMG	$\overline{\beta}_{i,1}^{UM}$
	Low income	Eq. (5.9)	LIN dataset	CCEMG	$\overline{\beta}_{i,1}^{LI}$
	High income	Eq. (5.9)	HIN dataset	OLS	β_{1}^{HI}
	[B] Geographical region:				
	Sub-Saharan Africa	Eq. (5.9)	SSA dataset	CCEMG	$\overline{\beta}_{i,1}^{SSA}$
	North Africa	Eq. (5.9)	NA dataset	CCEMG	$\overline{\beta}_{i,1}^{NA}$
	[C] Fragility status:				
	Fragile countries	Eq. (5.9)	Fragile dataset	CCEMG	$\overline{\beta}_{i,1}^{FA}$
	Non-fragile countries	Eq. (5.9)	Non-fragile dataset	CCEMG	$\overline{\beta}_{i,1}^{NFA}$

Note: LMI = Lower middle income group; UMI = Upper middle income group; LIN = Lower income group; HIN = High income group; SSA = Sub-Saharan Africa; NA = North Africa; FA = Fragile group; NFA = Non-fragile group

5.6.9 Descriptive Analysis

Descriptive statistics (annual values across countries) are presented in Table 5.8. The health expenditure and income variables have more variation than other indicators used in this study. For instance, real total health expenditure per capita has a mean of $208.6 and ranges from $5.94 (Congo Democratic Republic) to $1,768.7 (Equatorial Guinea). Government expenditure averages $114.5 per person. On average, each person spends $66.3 annually out of their disposable income (excluding private insurance contribution) to access healthcare services. Mauritius has the highest out-of-pocket health expenditure per capita (at $416.1) while Mozambique has the lowest ($2.37). Real GDP per capita has a mean of $2,335.2 with a maximum of $25,732.7 (Equatorial Guinea) and a minimum of $115.4 (Liberia).

The demographic and health status variables display less variation across countries within the considered years and sampled countries. The average shares of the population younger than 15 and older than 64 are 41.4% and 3.50%, respectively. Life expectancy at birth has a mean of 56.5 years with a minimum of 31.6 years (Rwanda) and a maximum of 74.8 years (Algeria). Infant mortality ranges from 11.9 per 1,000 live births (Liberia) to 158.3 (Libya).

Most of the African countries in the sample are net recipients of foreign aid and ODA with a mean of $65.5 per person and a maximum of $1,052.9 per capita (in Seychelles). Equatorial Guinea is the only African country that donated more than they received (-$16.3) during the sample period.

Table 5.8: Descriptive Statistics

Variable	Obs	Mean	Std Dev	Min	Max
Real Total Health expenditure per capita ($) (THE)	932	208.6	245.3	5.94	1,768.7
Real Government Health expenditure per capita ($) (GHE)	932	114.5	168.6	0.18	1,483.0
Real Out-of-pocket Health expenditure per capita ($) (OPE)	932	66.3	74.2	2.37	416.1
Real GDP per capita ($) (GDP)	930	2,335.2	3,457.2	115.4	25,732.7
Life expectancy at birth (in years) (LEX)	934	56.5	8.14	31.6	74.8
Infant mortality (per 1,000 live births) (INM)	940	68.7	30.4	11.9	158.3
Population aged less than 15 (% of total) (P15)	937	41.4	6.29	19.8	50.4
Population aged 65 and above (% of total) (P65)	937	3.50	1.22	1.70	9.13
Real net ODA and official aid received per capita ($) (ODA)	937	63.6	65.5	-16.3	1,052.9
Government final consumption expenditure (% of GDP) (GFC)	913	15.4	7.09	2.05	69.5

NOTE: The sample consists of annual data for years 1995-2014 from 47 African countries.

The average size of total government resources available for allocation across sectors of the economy (including health) is 15.4% of GDP. It ranges from 2.05% (Zimbabwe) to 69.5% (Eritrea). Data from the World Bank (2017) WDI indicates that public health spending as a share of total government expenditure ranges from 1.6% (Congo Dem. Rep.) to 28.2% (Tanzania) -- with an average share of 9.7% between 1995 and 2014. Some African countries (such as Tanzania, Malawi, Central African Republic, Ethiopia, Rwanda, Liberia, Chad, Uganda, Congo Democratic Republic and Burkina Faso) in some years allocated more than twice the average share to the health sector. Often, this can be traced to periods of debt cancellation by the African Development Bank, civil conflicts, boarder disputes, inter-country war, and increases in health-conditioned ODA.

5.6.9 Pre-Estimation Diagnostics Results

The cross-sectional dependence and panel unit root properties of the health expenditure, income and demographic variables used in this study are examined and the corresponding results are shown in Table 5.9. Pesaran's (2004) cross-sectional correlation test results reveal high absolute off-diagonal correlation coefficients ranging from 0.60 to 0.94 for health expenditures (lnTHE and lnGHE), income (lnGDP), health status (lnLEX and lnINM), and demographic (lnP15 and lnP65) panel series. Out-of-pocket health expenditure per capita (lnOPE), ODA per capita (lnODA) and government fiscal capacity (lnGFC) series appear to be less correlated across countries. The null hypothesis of "cross-sectional independence" is, however, rejected for all variables.

Using the CIPS test by Pesaran (2007) that (correctly) assumes cross-sectional dependence, the null hypothesis of "non stationarity" is rejected for health expenditures (total, government, and out-of-pocket) per capita, income per capita, life expectancy at birth, and ODA per capita. The rejection of the CIPS null hypothesis indicates that it is only a fraction of the countries not all the panel units have stationary series (Pesaran, 2012). The infant mortality rate, government fiscal capacity, population aged less than 15, and the share of ageing population series are shown to be non-stationary at level when using the CIPS. This implies that cross-sectionally correlated, stationary as well as non-stationary variables are used in this study. This motivates the use of a robust estimation method, the CCEMG, as the baseline estimators in subsequent sections.

5.7 Results and Discussion

The baseline panel model (5.9) for total health expenditure, government health spending and out-of-pocket health expenditure is estimated using CCEMG (Table 5.10). Afterwards, post estimation diagnostics and robustness tests are performed to determine the reliability and consistency of the baseline income elasticity estimate to changes in model specification, estimation methods, and data decomposition. These include: baseline model re-specification without a linear time trend (Table 5.11); sample decomposition by exchange rate variation (Table 5.12); different estimation methods (Table 5.13); and sample decomposition by income group (Table 5.14), geographical region (Table 5.15), and fragility status (Table 5.16). In addition, the summary of all the income elasticities estimated in this chapter for each of the health expenditure variables is shown in Table 5.17. The associated lower and upper confidence intervals at the 95% significance level in Table 5.17 are used to create floating bar plots presented in Figures 5.7. 5.8, and 5.9.

The empirical results for each of the three categories of health expenditure are discussed below.

5.7.1 Total Health Expenditure

Income: Changes in real GDP per capita have a positive and significant effect on changes in real total health expenditure per capita (Table 5.10, column 1). For a 1% increase in income, total health expenditure significantly increases by 0.58%, on average. Therefore, the results indicate that health is income inelastic and a necessity good. Also, when formally

Table 5.9: Pre-Estimation Diagnostics Test Results

	Pesaran (2004) CD Test		*Maddala & Wu (1999) PURT*				*Pesaran (2007) CIPS PURT*			
			Level		*FD*		*Level*		*FD*	
	CD_{PES}	$\lvert\bar{\hat{\rho}}\rvert$	*No Trend*	*Trend*	*No Trend*	*Trend*	*No Trend*	*Trend*	*No Trend*	*Trend*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
ln(THE)	83.0***	0.659	1	1	0***	0***	0***	0**	0***	0***
ln(GHE)	79.79***	0.611	1	1	0***	0***	0***	0*	0***	0***
ln(OPE)	31.41***	0.497	1	1	0***	0***	0***	1	0***	0***
ln(GDP)	51.44***	0.610	1	1	0***	0***	0***	1	0***	0***
ln(LEX)	113.1***	0.847	0***	0***	0***	0***	0***	0***	0***	0***
ln(INM)	133.7***	0.941	0***	0***	0***	1	1	1	0*	1
ln(P15)	58.69***	0.712	0***	0***	0**	0***	1	1	1	1
ln(P65)	-1.24***	0.697	0***	0***	0***	0***	1	1	1	1
ln(ODA)	8.12***	0.315	0***	0***	0***	0***	0***	0*	0***	0***
ln(GFC)	4.00***	0.349	0***	0***	0***	0***	1	1	0***	0***

Note: CD = Cross-sectional dependence; PURT = Panel Unit Root Test; CIPS = Cross-sectional augmented Im, Pesaran & Shin (2003); FD = First Difference; $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series; CD_{PES} = Pesaran (2004) CD test; Null hypothesis for Maddala & Wu (1999) and Pesaran (2007) CIPS tests is "no stationarity" i.e. series is I(1); MW test assumes cross-section independence; CIPS test assumes cross-sectional dependence in form of a single unobserved common factor. * 10%, ** 5%, and *** 1% significance level respectively; 1 = Not stationary, i.e. series is I(1); 0 = Stationary, i.e. series is I(0). Lag 1 is used for all the PURTs. For the colour highlight, red indicates variables that are both stationary at level and FD, while green is for series that are only stationary at FD.

Table 5.10: Baseline Results - Income Elasticity of Healthcare Expenditures

Variable	*Baseline*		
	lnTHE ***(1)***	***lnGHE*** ***(2)***	***lnOPE*** ***(3)***
Real GDP per capita (lnGDP)	0.582* (1.67)	1.375** (2.42)	1.131** (2.36)
Life expectancy (lnLEX)	-4.424 (-0.70)	-15.64 (-1.26)	-3.167 (-0.41)
Infant mortality (lnINM)	-5.583 (-1.46)	-4.978 (-1.38)	-3.128 (-0.95)
Population aged > 64 (lnP65)	-4.341 (-1.41)	-2.140 (-0.46)	-0.711 (-0.19)
Population aged < 15 (lnP15)	2.763 (0.63)	-12.88 (-1.35)	1.456 (0.22)
Real net ODA per capita (lnODA)	0.0209 (0.54)	0.00854 (0.16)	-0.00762 (-0.25)
Government expenditure/GDP (lnGFC)	0.167 (1.61)	0.441*** (3.23)	0.0735 (0.66)
Trend	-0.037 (-0.38)	-0.179 (-1.10)	0.071 (0.69)
Obs.	896	896	896
N	47	47	47
RMSE	0.030	0.055	0.039
AIC	-2687.3	-2223.3	-2484.8
$\lvert\hat{\bar{\rho}}\rvert$	0.293	0.296	0.299
CD_{PES}	-0.69	-1.39	-0.71
CIPS PURT (Residual)	I(0)	I(0)	I(0)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\lvert\hat{\bar{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.11: Robustness Check #1 -- Model Re-Specification without Trends and Pedroni's Cointegration Test

Variable	***Baseline Model without Trends***		
	lnTHE (1)	***lnGHE (2)***	***lnOPE (3)***
Real GDP per capita (lnGDP)	0.570 (1.61)	1.206** (2.24)	1.174*** (3.13)
Life expectancy (lnLEX)	-9.385* (-1.65)	-23.17** (-2.10)	-1.245 (-0.29)
Infant mortality (lnINM)	-1.791 (-0.81)	-5.784* (-1.75)	0.349 (0.20)
Population aged > 64 (lnP65)	-2.533 (-0.99)	-0.766 (-0.16)	-0.277 (-0.10)
Population aged < 15 (lnP15)	-0.0125 (-0.01)	2.362 (0.34)	-5.931* (-1.91)
Real net ODA per capita (lnODA)	0.0390 (1.29)	-0.00882 (-0.17)	0.00825 (0.28)
Government expenditure/GDP (lnGFC)	0.231** (2.48)	0.384*** (2.77)	0.125 (1.54)
Trend	----	----	----
Obs.	896	896	896
N	47	47	47
RMSE	0.034	0.062	0.043
AIC	-2592.8	-2137.1	-2413.2
$\left\|\hat{\bar{\rho}}\right\|$	0.286	0.287	0.289
CD_{PES}	-2.15**	-1.57	-1.92*
CIPS PURT (Residual)	I(0)	I(0)	I(0)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\left|\hat{\bar{\rho}}\right|$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.11.1: Pedroni's (2004) Coinetgration Tests

Statistic	***Pedroni's (2004) Cointegration Tests***		
	lnTHE (1)	***lnGHE (2)***	***lnOPE (3)***
Panel: v	-5.9***	-4.781***	-4.957***
Panel: rho	5.904***	6.044***	6.379***
Panel: t	-15.15***	-12.78***	-11.64***
Panel: ADF	11.27***	5.918***	1.105
Group: rho	8.756***	8.937***	9.366***
Group: t	-19.1***	-15.6***	-14.41***
Group: ADF	11.87***	11.79***	5.239***
N	47	47	47
T (average per unit)	19	19	19
Number of Regressors	7	7	7
Standardised Critical Values (one-tail):	1%	5%	10%
	2.326	1.645	1.282
Null Hypothesis: "No Cointegration"	Reject	Reject	Reject

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). All the regressors in Equation (5.10) are used for this test. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.12: Robustness Check #2 -- Country Split by Exchange Rate Variation

Variable	*Stable PPP*			*Unstable PPP*		
	lnTHE (1)	***lnGHE (2)***	***lnOPE (3)***	***lnTHE (4)***	***lnGHE (5)***	***lnOPE (6)***
Real GDP per capita (lnGDP)	0.867** (2.49)	1.570** (2.49)	0.859* (1.93)	0.785 (1.09)	4.384 (0.89)	0.747** (2.24)
Life expectancy (lnLEX)	-5.183 (-0.79)	-7.856 (-0.74)	5.059 (1.06)	-5.098 (-0.14)	-72.54* (-1.69)	61.97** (2.08)
Infant mortality (lnINM)	-7.212* (-1.88)	-6.691 (-1.64)	0.279 (0.08)	-8.092 (-1.02)	14.18 (0.35)	-8.139 (-0.54)
Population aged > 64 (lnP65)	-6.075* (-1.89)	-4.984 (-0.56)	-4.175 (-1.10)	-28.15 (-1.58)	-94.26*** (-2.59)	-10.97 (-0.69)
Population aged < 15 (lnP15)	6.610* (1.70)	-7.390 (-0.61)	5.693 (1.02)	-84.48 (-1.41)	-62.02 (-0.47)	-29.60 (-0.74)
Real net ODA per capita (lnODA)	0.00581 (0.16)	0.0278 (0.68)	-0.0014 (-0.05)	0.0043 (0.09)	-0.0417 (-0.33)	-0.0968 (-1.00)
Government expenditure/GDP (lnGFC)	0.135 (1.42)	0.425*** (2.81)	0.0704 (0.69)	0.332*** (3.39)	0.409 (0.88)	-0.124 (-0.68)
Trend	0.00427 (0.06)	-0.192 (-1.35)	0.0519 (0.74)	-0.224 (-0.47)	1.701 (1.10)	-0.475 (-0.89)
Obs.	756	756	756	140	140	140
N	40	40	40	7	7	7
RMSE	0.026	0.042	0.037	0.032	0.080	0.036
AIC	-2357.5	-2055.5	-2127.3	-385.3	-273.7	-371.6
$\left\|\bar{\hat{\rho}}\right\|$	0.293	0.297	0.312	0.299	0.28	0.287
CD_{PES}	-1.02	-0.14	-0.13	0.57	-0.73	-0.57
CIPS PURT (Residual)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\left|\bar{\hat{\rho}}\right|$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.13: Robustness Check #3 -- Estimation Methods

Variable	*Pooled OLS*			*Two-Way Fixed Effect*			*AMG*		
	lnTHE (1)	***lnGHE (2)***	***lnOPE (3)***	***lnTHE (4)***	***lnGHE (5)***	***lnOPE (6)***	***lnTHE (7)***	***lnGHE (8)***	***lnOPE (9)***
Real GDP per capita (lnGDP)	0.851*** (21.43)	0.828*** (11.91)	0.800*** (15.18)	0.743*** (6.96)	0.959*** (4.18)	0.678*** (5.36)	0.847*** (3.92)	1.357*** (3.88)	0.832*** (2.88)
Life expectancy (lnLEX)	0.406*** (2.72)	0.254 (0.95)	0.224 (0.78)	-0.0185 (-0.04)	0.235 (0.23)	0.0406 (0.05)	-0.00534 (-0.00)	-1.722 (-0.25)	-3.052 (-0.97)
Infant mortality (lnINM)	-0.366*** (-4.27)	-0.224 (-1.58)	-0.530*** (-3.73)	-0.464 (-1.45)	-0.488 (-0.86)	-0.0892 (-0.26)	-1.853 (-1.19)	-0.742 (-0.42)	-2.120 (-1.50)
Population aged > 64 (lnP65)	0.266** (2.12)	0.225 (1.08)	0.186 (0.85)	0.0742 (0.11)	-0.160 (-0.17)	-0.199 (-0.30)	-4.172*** (-2.70)	-5.741* (-1.77)	-2.518 (-1.29)
Population aged < 15 (lnP15)	-0.387 (-1.59)	0.301 (0.85)	-0.969** (-2.15)	0.750 (0.98)	0.736 (0.79)	-0.404 (-0.39)	2.985 (1.15)	0.433 (0.09)	3.752 (0.87)
Real net ODA per capita (lnODA)	0.0410*** (3.24)	0.116*** (5.40)	0.0358** (1.99)	0.0377* (1.94)	0.0718** (2.31)	0.0248 (1.32)	0.0168 (0.92)	0.0412 (1.17)	-0.0173 (-1.18)
Government expenditure/GDP (lnGFC)	0.218*** (6.33)	0.459*** (5.80)	0.174*** (3.40)	0.194*** (3.57)	0.429*** (3.13)	0.116 (1.36)	0.100* (1.87)	0.302*** (3.13)	0.0736 (1.38)
Trend	0.0148*** (5.44)	0.0353*** (7.69)	-0.0111*** (-2.88)	0.0588*** (2.87)	0.0574* (1.94)	0.0562** (2.27)	-0.0284 (-0.57)	-0.121 (-1.59)	-0.0014 (-0.03)

Variable	*Pooled OLS* lnTHE (1)	*Pooled OLS* lnGHE (2)	*Pooled OLS* lnOPE (3)	*Two-Way Fixed Effect* lnTHE (4)	*Two-Way Fixed Effect* lnGHE (5)	*Two-Way Fixed Effect* lnOPE (6)	*AMG* lnTHE (7)	*AMG* lnGHE (8)	*AMG* lnOPE (9)
Obs.	896	896	896	896	896	896	886	886	886
N	47	47	47	47	47	47	46	46	46
RMSE	0.175	0.298	0.249	0.140	0.241	0.176	0.065	0.104	0.078
AIC	-530.7	429.3	103.9	-1040.7	-212.5	-631.5	-2089.5	-1719.6	-1945.2
$\lvert\bar{\hat{\rho}}\rvert$	0.376	0.356	0.421	0.314	0.336	0.313	0.222	0.23	0.226
CD_{PES}	0.5	-0.28	1.70 *	3.02**	1.72*	1.68*	-1.94*	-2.05**	-1.21
CIPS PURT (Residual)	I(1)	I(0)	I(1)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.14: Robustness Check #4 -- Data Decomposition by Income Group

	Lower Middle Income			***Upper Middle Income***			***Low Income***			***High Income***		
Variable	***lnTHE (1)***	***lnGHE (2)***	***lnOPE (3)***	***lnTHE (4)***	***lnGHE (5)***	***lnOPE (6)***	***lnTHE (7)***	***lnGHE (8)***	***lnOPE (9)***	***lnTHE (10)***	***lnGHE (11)***	***lnOPE (12)***
Real GDP per capita (lnGDP)	0.322 (0.40)	0.750 (0.52)	-2.108 (-1.41)	-0.176 (-0.19)	-0.444 (-0.33)	0.261 (0.24)	0.635 (1.23)	0.684 (0.79)	0.778 (1.48)	0.665 (0.84)	0.757 (0.94)	1.175 (1.23)
Life expectancy (lnLEX)	4.281 (0.44)	-71.72 (-1.28)	-27.82 (-1.45)	0.716* (1.75)	-0.819 (-0.11)	-0.106 (-0.03)	4.816 (0.39)	-3.604 (-0.19)	4.187 (0.43)	-5.776 (-1.11)	-6.064 (-1.16)	-4.612 (-0.82)
Infant mortality (lnINM)	-11.91* (-1.90)	-17.0*** (-2.64)	-10.8* (-1.86)	-1.145** (-2.46)	1.615 (0.70)	-0.835 (-0.96)	4.024 (1.49)	-1.034 (-0.13)	0.115 (0.03)	13.34 (1.07)	15.60 (1.27)	3.354 (0.32)
Population aged > 64 (lnP65)	-16.9** (-1.98)	2.712 (0.25)	-10.10 (-1.40)	-0.526 (-0.11)	0.484 (0.25)	-3.177** (-2.15)	-19.0** (-1.96)	-15.16 (-1.53)	4.430 (0.35)	-1.853 (-0.73)	-2.553 (-0.99)	9.105* (2.41)
Population aged < 15 (lnP15)	-6.286 (-0.31)	-23.25 (-0.61)	-16.08 (-0.49)	0.715 (0.41)	0.699 (0.28)	-2.178 (-0.58)	7.280 (0.45)	16.24 (0.76)	-5.129 (-0.38)	6.192 (1.96)	6.135 (1.95)	0.734 (0.32)
Real net ODA per capita (lnODA)	0.0410 (1.11)	0.0362 (0.57)	0.0283 (0.93)	-0.00321 (-0.10)	0.0229 (0.54)	-0.135** (-2.21)	0.0392 (0.61)	-0.132 (-1.22)	-0.0064 (-0.11)	0.122 (1.11)	0.108 (0.99)	-0.0457 (-0.60)
Government expenditure/GDP (lnGFC)	0.216 (1.11)	0.362 (0.74)	0.193 (0.93)	0.159 (0.62)	0.407 (1.07)	0.0404 (0.21)	0.0521 (0.87)	0.0818 (0.73)	-0.0891 (-0.64)	0.0873 (0.33)	0.111 (0.41)	0.0917 (0.51)
Trend	-0.243 (-0.89)	-0.0572 (-0.09)	-0.265 (-0.78)	0.0172 (0.20)	0.0309 (0.43)	-0.225 (-0.90)	0.124 (0.67)	-0.0128 (-0.03)	0.157 (0.64)	0.121 (1.93)	0.122 (1.94)	-0.0664 (-1.32)

	Lower Middle Income			*Upper Middle Income*			*Low Income*			*High Income*		
Variable	***lnTHE (1)***	***lnGHE (2)***	***lnOPE (3)***	***lnTHE (4)***	***lnGHE (5)***	***lnOPE (6)***	***lnTHE (7)***	***lnGHE (8)***	***lnOPE (9)***	***lnTHE (10)***	***lnGHE (11)***	***lnOPE (12)***
Obs.	253	253	253	163	163	163	466	466	466	14	14	14
N	13	13	13	9	9	9	24	24	24	1	1	1
RMSE	0.026	0.043	0.032	0.025	0.038	0.048	0.027	0.058	0.024	0.141	0.141	0.133
AIC	-768.9	-656.4	-723.1	-489.4	-429.4	-395.6	-1431.0	-1115.7	-1469.0	-11.5	-11.6	-15.1
$\lvert\bar{\hat{\rho}}\rvert$	0.31	0.295	0.266	0.306	0.283	0.328	0.329	0.307	0.312	0.924	0.915	0.729
CD_{PES}	-0.06	2.21**	-0.65	0.63	-0.82	-0.19	0	-0.75	-0.95	129.66***	128.53***	68.42***
CIPS PURT (Residual)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(1)	I(1)	I(1)

<u>NOTE</u>: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.15: Robustness Check #5: Data Decomposition by Geographical Region

Variable	*Sub-Saharan Africa (SSA)*			*North Africa*		
	***lnTHE* (1)**	***lnGHE* (2)**	***lnOPE* (3)**	***lnTHE* (4)**	***lnGHE* (5)**	***lnOPE* (6)**
Real GDP per capita (lnGDP)	0.228 (0.52)	0.942 (1.63)	0.619 (1.48)	0.695 (0.29)	0.462 (0.14)	0.487 (0.26)
Life expectancy (lnLEX)	-4.129 (-0.75)	0.507 (0.04)	2.938 (0.44)	-1.466 (-0.26)	-10.87 (-1.38)	1.787 (0.52)
Infant mortality (lnINM)	0.654 (0.19)	5.907 (1.23)	-5.925 (-1.46)	3.835 (0.39)	2.901 (0.29)	-3.836 (-1.04)
Population aged > 64 (lnP65)	-5.090 (-1.25)	-0.358 (-0.04)	-7.316 (-1.32)	1.604 (0.40)	-0.637 (-0.72)	5.168 (0.82)
Population aged < 15 (lnP15)	11.37 (1.43)	-13.75 (-0.89)	3.752 (0.29)	1.318 (0.14)	2.662 (0.23)	-8.605 (-0.84)
Real net ODA per capita (lnODA)	0.0319 (0.86)	-0.0471 (-0.73)	-0.0146 (-0.33)	-0.0177 (-0.36)	0.00263 (0.03)	-0.0432 (-0.68)
Government expenditure/GDP (lnGFC)	0.260*** (2.60)	0.524*** (3.41)	0.00686 (0.06)	-0.0958 (-0.26)	0.227 (0.37)	-0.762* (-1.71)
Trend	-0.00550 (-0.05)	0.0851 (0.42)	-0.0897 (-1.07)	0.663 (1.05)	-0.200 (-0.60)	0.114 (0.91)
Obs.	793	793	793	103	103	103
N	41	41	41	6	6	6
RMSE	0.026	0.046	0.039	0.010	0.016	0.011
AIC	-14.1	-13.1	-12.1	-11.1	-10.1	-9.1
$\lvert\bar{\hat{\rho}}\rvert$	0.306	0.312	0.325	0.311	0.301	0.281
CD_{PES}	-0.95	-1.06	-0.48	-1.05	-1.35	-1.19
CIPS PURT (Residual)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\lvert\bar{\hat{\rho}}\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.16: Robustness Check #6 -- Data Decomposition by Fragility Status

Variable	*Fragile States*			*Non-Fragile States*		
	***lnTHE* (1)**	***lnGHE* (2)**	***lnOPE* (3)**	***lnTHE* (4)**	***lnGHE* (5)**	***lnOPE* (6)**
Real GDP per capita (lnGDP)	1.270*** (3.51)	1.893*** (2.58)	1.179** (2.47)	0.640 (0.97)	0.0699 (0.06)	0.289 (0.34)
Life expectancy (lnLEX)	8.724 (1.16)	11.72 (0.58)	9.190 (0.64)	3.347 (0.63)	40.59 (1.56)	24.32 (1.20)
Infant mortality (lnINM)	0.786 (0.15)	2.443 (0.26)	-2.412 (-0.79)	-9.87** (-2.10)	-2.895 (-0.60)	-4.084 (-0.88)
Population aged > 64 (lnP65)	2.173 (0.28)	8.668 (1.12)	5.934 (0.92)	3.261 (0.51)	3.764 (0.89)	-8.441 (-0.92)
Population aged < 15 (lnP15)	-6.832 (-0.78)	9.154 (0.61)	1.615 (0.21)	-4.626 (-0.53)	3.158 (0.35)	-11.75 (-1.20)
Real net ODA per capita (lnODA)	-0.00684 (-0.20)	-0.0436 (-0.79)	0.00158 (0.06)	0.0275 (0.92)	0.0917* (1.67)	0.0341 (0.35)
Government Expenditure/GDP (lnGFC)	0.0652 (0.55)	0.498*** (2.70)	-0.0171 (-0.14)	0.264 (1.44)	0.157 (0.75)	0.00860 (0.05)
Trend	-0.00307 (-0.02)	0.0933 (0.43)	0.0899 (0.55)	-0.264* (-1.76)	-0.338* (-1.91)	-0.0802 (-0.46)
Obs.	545	545	545	351	351	351
N	29	29	29	18	18	18
RMSE	0.028	0.055	0.033	0.033	0.043	0.038
AIC	-8.1	-7.1	-6.1	-5.1	-4.1	-3.1
$\left\lvert\bar{\hat{\rho}}\right\rvert$	0.297	0.315	0.305	0.304	0.295	0.293
CD_{PES}	0.23	-0.64	1	-2.09 **	-2.33**	-0.85
CIPS PURT (Residual)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)

NOTE: Dependent variables: THE (Real total health expenditure per capita); GHE (Real government health expenditure per capita); and OPE (Real out-of-pocket health expenditure per capita). RMSE = Root mean squared error. AIC = Akaike Information Criteria. $\left\lvert\bar{\hat{\rho}}\right\rvert$ = average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the series. CD_{PES} = Pesaran (2004) cross-sectional dependence (CD) test. Cross-sectionally augmented Im, Pesaran & Shin (2003) panel unit root test (PURT) at lag 1 is used as a residual based cointegration test. I(0) indicates the relationship is cointegrated and the residual is stationary at level. I(1) = Non-stationary and not cointegrated. Unless otherwise noted, numbers in parentheses are *z*-statistics corresponding to coefficient estimates. All the estimation used robust standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5.17: Summary -- Income Elasticity of Health Expenditures Per Capita

Models	***THE***				***GHE***				***OPE***			
	Parameter	***Income Elasticity***	***Lower CI***	***Upper CI***	***Parameter***	***Income Elasticity***	***Lower CI***	***Upper CI***	***Parameter***	***Income Elasticity***	***Lower CI***	***Upper CI***
Baseline	B1	0.582*	-0.100	1.263	C1	1.375**	0.263	2.487	D1	1.131**	0.193	2.069
Specification Without Trend	B2	0.570	-0.122	1.262	C2	1.206**	0.149	2.263	D2	1.174***	0.438	1.909
Stable PPP	B3	0.867***	0.185	1.549	C3	1.570***	0.334	2.806	D3	0.859***	-0.013	1.731
Unstable PPP	B4	0.785	-0.627	2.198	C4	4.384	-5.295	14.064	D4	0.747**	0.094	1.400
POLS	B5	0.851***	0.773	0.929	C5	0.828***	0.692	0.965	D5	0.800***	0.696	0.903
2WFE	B6	0.743***	0.528	0.958	C6	0.959***	0.498	1.421	D6	0.678***	0.423	0.933
AMG	B7	0.847***	0.424	1.271	C7	1.357***	0.672	2.041	D7	0.832***	0.266	0.266
Low Middle Income	B8	0.322	-1.262	1.906	C8	0.750	-2.061	3.560	D8	-2.108	-5.040	0.824
Upper Middle Income	B9	-0.176	-2.007	1.655	C9	-0.444	-3.078	2.190	D9	0.261	-1.903	2.426
Low Income	B10	0.635	-0.380	1.651	C10	0.684	-1.011	2.380	D10	0.778	-0.249	1.806
High Income	B11	0.665	-1.380	2.710	C11	0.757	-1.319	2.833	D11	1.175	-1.288	3.638
SSA	B12	0.228	-0.636	1.093	C12	0.942	-0.188	2.072	D12	0.619	-0.202	1.440
North Africa	B13	0.695	-3.934	5.323	C13	0.462	-6.141	7.065	D13	0.487	-3.135	4.109
Fragile States	B14	1.270***	0.560	1.979	C14	1.893***	0.454	3.331	D14	1.179**	0.245	2.114
Non-Fragile States	B15	0.640	-0.650	1.930	C15	0.070	-2.265	2.405	D15	0.289	-1.386	1.963

CI = Confidence Interval at 95% level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

tested using confidence intervals (see Table 5.17 and Figure 5.7), it indicates that the income elasticity coefficients from most of the estimators are less than one."

Health status: Life expectancy at birth and infant mortality have insignificant effects on total health expenditure per capita. The signs of the effects contradict the theoretical expectations.

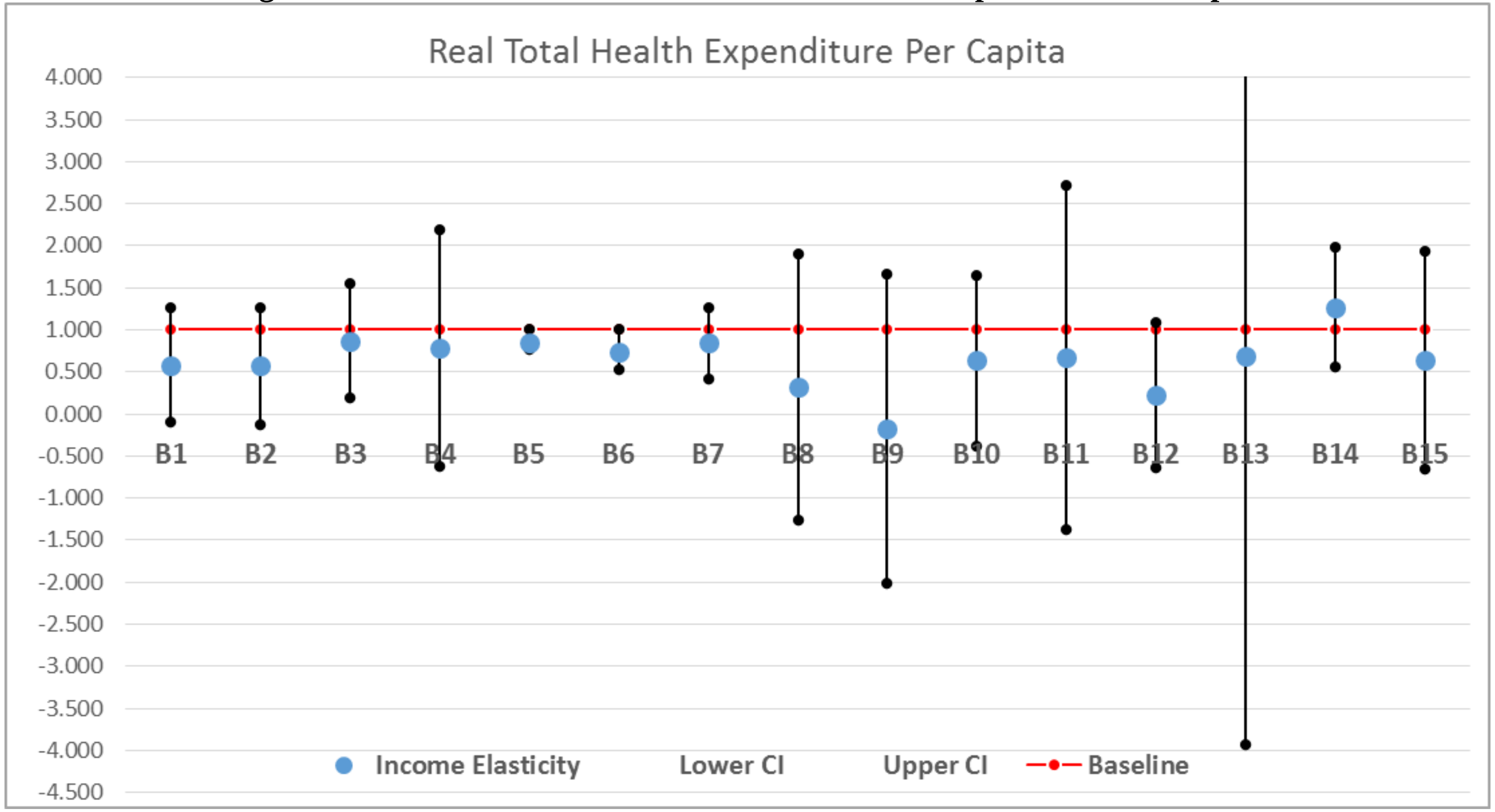
Demographic structure: The share of the population younger than 15 has an insignificant effect on real total health expenditure per capita. Likewise, an increase in the share of the elderly is not statistically significant.

Net foreign aid and ODA received: Overall, net foreign aid and ODA received for health and non-health programmes per capita is positively associated with total healthcare spending. However, the relationship is statistically insignificant.

Government fiscal capacity: The total final government consumption as a share of GDP is positively related to total health spending contributions from both the private and public sectors of the economy. However, the effect is again statistically insignificant.

Robustness checks: As shown in Table 5.17 and Figure 5.7, the income elasticity coefficient of total health expenditure from the baseline model (0.582) is found robust to almost all considered checks. An important exception is the sub-sample of fragile states which yields an income elasticity estimate of 1.270, i.e., greater than one (see Table 5.16). This implies that the sum of public and private health expenditures grows faster than income in African countries that experience intense fragility emanating from a high poverty rate, unequal access to quality healthcare services, and civil war. According to Akaike Information Criteria (AIC) values of the analysed 15 models, the baseline model performs the best. Also, the residual series generated from the baseline specification are cross-sectionally independent and stationary at level based on the results from Pesaran's (2004) CD test and Pesaran's (2007) CIPS PURT.

Figure 5.7: Income Elasticities of Real Total Health Expenditure Per Capita



5.7.2 Government Healthcare Expenditure

Income. Public health expenditure as a component of total health spending is positively associated with real GDP per capita as a measure of income. As shown in Table 5.10 (column 2) the income elasticity coefficient is 1.375 and is statistically significant at the 5% significance level. This indicates that public budget allocation to the health sector grows by 1.38% with a 1% change in real income, on average. Also, in formal testing using the reported confidence interval values in Table 5.17 and and Figure 5.8, it clearly shows that most of theincome elasticity estimates are less than one. This supports my findings that government health expenditure is not a luxury good.

Health status. As reported for total health expenditure, increases in life expectancy at birth and infant mortality lead to a decrease in public health spending on medical services. The effects are theoretically unexpected. However, they are not statistically significant.

Demographic structure. Changes in both young and elderly population as shares of total population have negative (but statistically insignificant) effects on government healthcare expenditure per capita. This again contradicts my expectations.

Net foreign aid and ODA received. Health and non-health conditioned aid and ODA received from abroad are positively related to changes in government medical expenditure across African countries. But again, the estimate is statistically insignificant and close to zero.

Government fiscal capacity. An increase in government consumption significantly increases government health care expenditure per capita. For a 1% increase in government fiscal capacity, public health spending increases by 0.44%.

Robustness checks. The elasticity estimate (1.375) from the baseline model estimation is robust to specifications that exclude a heterogeneous linear time trend, decompose the dataset and use different estimation methods (see Table 5.17 and Figure 5.8). The estimate for fragile African states is close 2.0, i.e., noticeably higher than the baseline estimate for the full sample.

However, the income elasticity estimate from the baseline and fragile states models are not statistically distinct ($Chi^2 = 0.50$, p-value = 0.4808).

Again, the baseline model has the lowest AIC value. The residual-based, post-estimation test results for model (5.10, column 2) suggest that CCEMG successfully addresses the issue of cross-section dependence.

5.7.3 Out-of-pocket health expenditure

Income: Real GDP per capita is positively and significantly associated with changes in out-of-pocket payments per person (Table 5.10, column 3). Increasing income by 1% leads to rise in out-of-pocket expenditure by 1.13%. However, the confidence interval values reported in Table 5.17 and Figure 5.9 show that the estimates coefficients are less than one. This indicates that out-of-pocket payment as health financing option makes health a necessity good..

Health status. The effects of life expectancy and infant mortality on out-of-pocket payment are negative and insignificant. Similar findings were reported for total healthcare expenditure and government health spending in columns 1 and 2 of Table 5.10.

Demographic structure. An increase in the share of population aged 65 and above causes out-of-pocket payment to decrease. This does not conform with theoretical expectation. On the other hand, an increase in the share of population aged less than 15 increases out-of-pocket payment. However, neither of the variables are statistically significant.

Net foreign aid and ODA received. Out-of-pocket health expenditure seems to be crowded-out by net foreign aid and ODA. This is plausible as an increase in net ODA reduces the burden on households by providing more coverage through the public sector. However, the estimate is statistically insignificant.

Government fiscal capacity. The ratio of government expenditure as a share of GDP positively influences out-of-pocket health expenditure per capita. This effect, while counterintuitive, is statistically insignificant.

Figure 5.8: Income Elasticities of Real Government Health Expenditure Per Capita

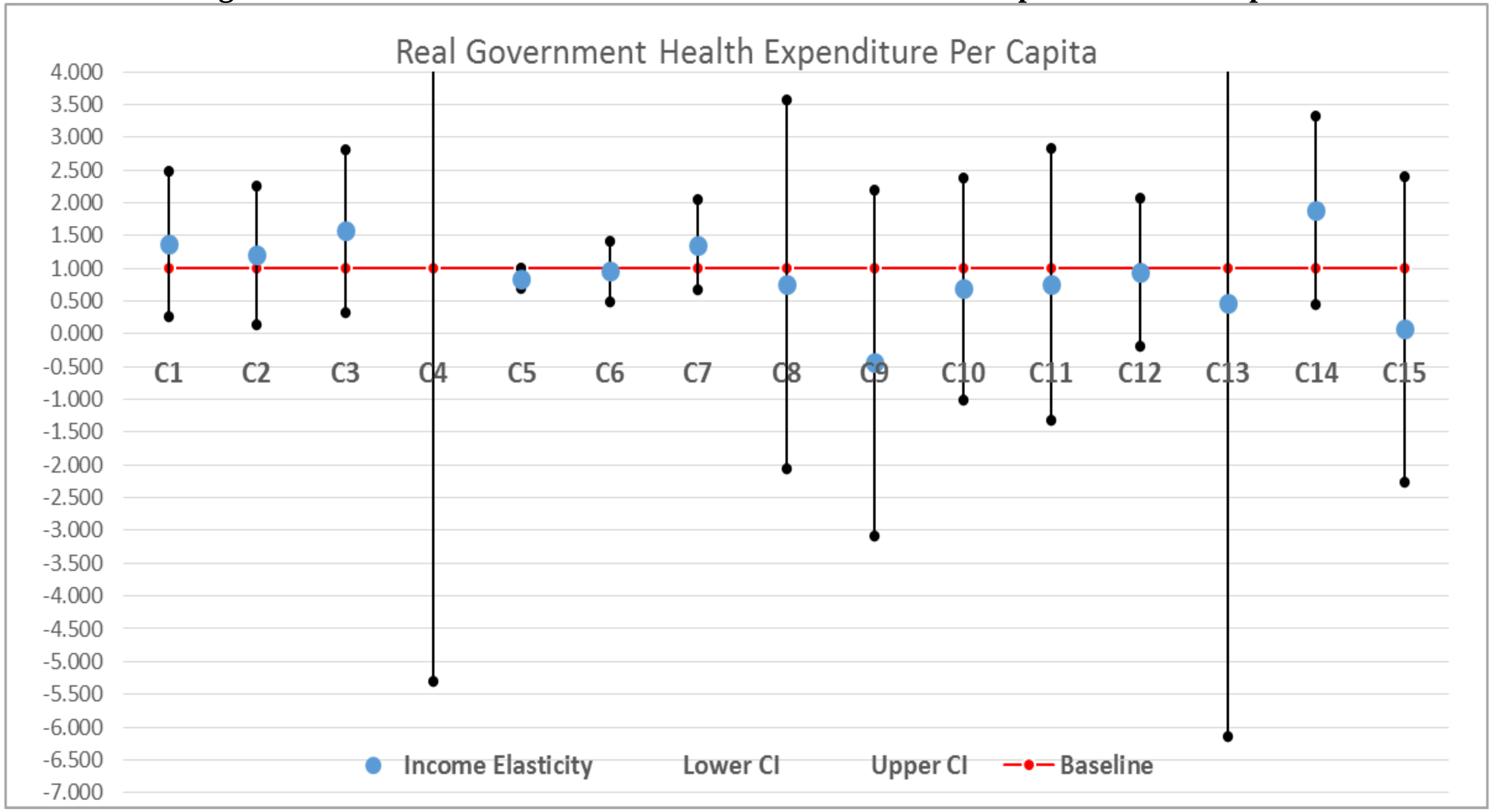
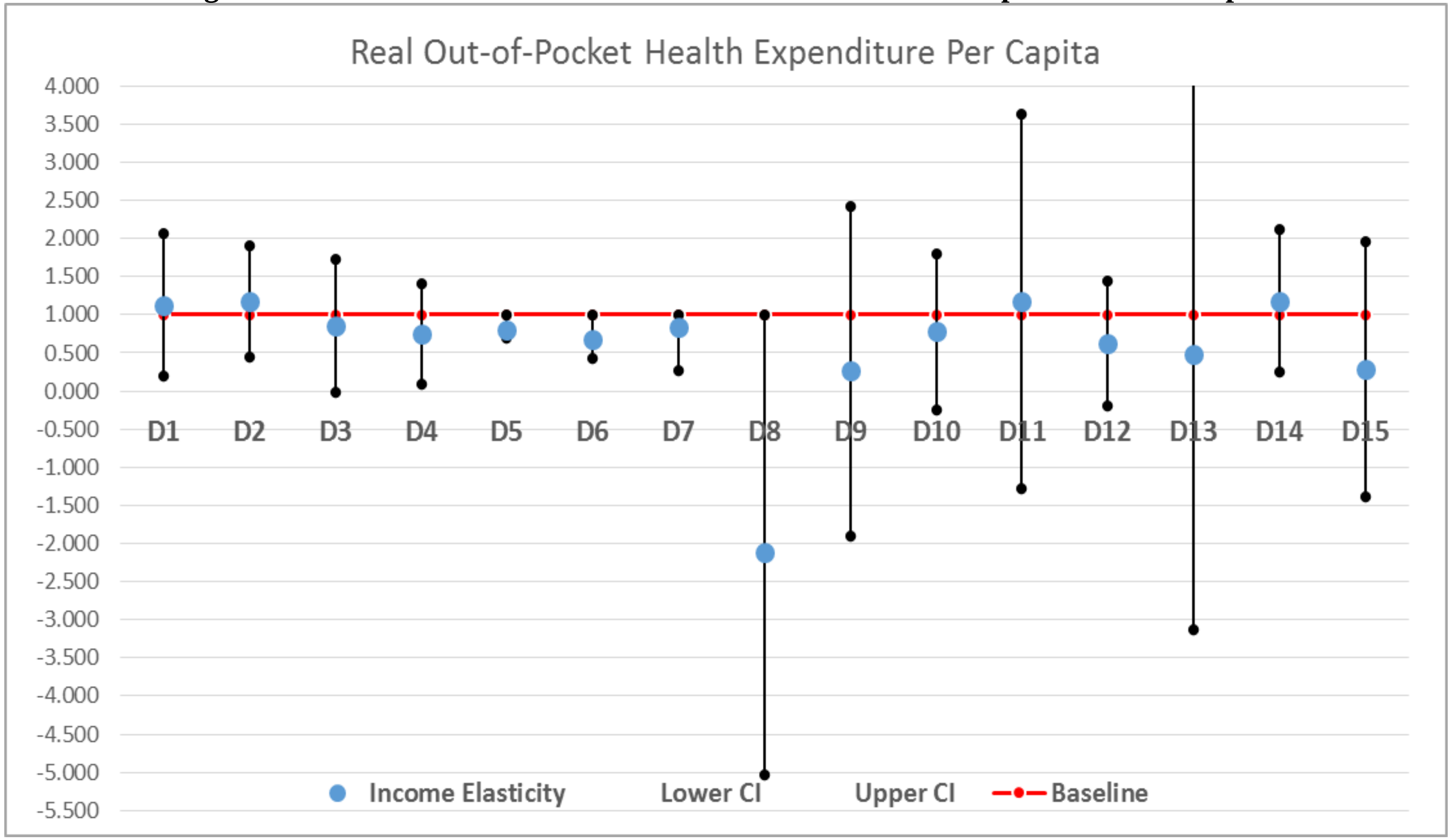


Figure 5.9: Income Elasticities of Real Out-of-Pocket Health Expenditure Per Capita



Robustness checks. Statistically significant estimates from robustness checks are similar to the baseline elasticity of 1.131 (Table 5.17 and Figure 5.9). A comparison of AIC values shows that the baseline specification is the best. The post estimation diagnostics test results in Table 5.10 reveal that the estimated residual series from the baseline model is cross-sectionally independent and stationary at level.

5.8 Summary, Conclusion and Recommendations

This chapter contributes to the existing literature on the income elasticity of health expenditure in Africa by: (i) investigating the income elasticity of public and private health expenditure separately; (ii) focusing on Africa, which has received limited attention in the past; (iii) being the first study, to the best of my knowledge, to examine the health-income nexus for fragile countries and primarily focusing on African countries characterised by low income, high poverty prevalence, deteriorating human welfare, high health burden, and a large official aid receipt; and (iv) carefully addressing data properties that make standard panel data estimators (POLS, FE, and 2WFE) biased.

The study sampled 47 out of 54 African countries for the period 1995-2014. The adopted baseline model regressed aggregate and disaggregated health care expenditures on measures of income, health status, demographic structure, net foreign aid, and government fiscal capacity. Results from Chapter 4 suggest CCEMG is the best estimator in a wide variety of data environments, and hence I use that for my baseline estimation[52].

Based on the baseline coefficient estimates, my findings suggest that total health expenditure is income inelastic, i.e., health care is a necessity good in the considered African countries as a group. This is consistent with the findings reported for Africa using cross-sectional data on total health spending (Gbesemete and Gerdtham (1992); Murthy (2004),

[52] The slope homogeneity test indicated that the null hypothesis “homogeneous income elasticity coefficient” is rejected at 1% significance level as shown in Table A5.2 (see the Appendix)

Okunade (2005), V. N. R. Murthy and A. A. Okunade (2009)), and panel data on aggregate health expenditure (Lv and Zhu (2014)). In regards to studies for other regions, my results complement the findings of Baltagi and Moscone (2010) that used a similar empirical model set-up for aggregate health spending across 20 OECD countries. But, my disaggregated analyses showed that public and private health expenditures are income elastic. This is consistent with the finding of Jaunky and Khadaroo (2008) that public health expenditure is a luxury good. Also, results for fragile African states yielded income elasticity coefficients greater than one. This is similar to the findings of J. A. Khan and Mahumud (2015) who employed a homogenous slope model set-up for South-East Asian countries in their disaggregated analysis.

Some of the non-income determinants (such as net ODA per capita and government fiscal capacity) were consistently found important across different model specifications. This is similar in spirit to the findings of Stubbs, Kentikelenis, Stuckler, McKee, and King (2017) for West African countries that ODA per capita significantly increases government health spending when there is instituted IMF policy conditioning the utilization of the aid for health programmes.

However, after accounting for different econometric issues and testing the hypotheses that health expenditures are either income elastic or inelastic for Africa, the overall results from the plots show strong support to conclude that health is a necessity good because the estimated coefficients from most of the models are below one. However, there is need for more data points across countries and model dataset using dynamic panel heterogeneous models.

Chapter 6: Summary, Conclusion and Areas of Further Research

Chapter Six

6.1 Introduction

This chapter provides brief summary of each of the analytical section of the thesis. This includes an overview of the identified problem, justification for the study, methods (data source, sample description, models and methods), key empirical results, conclusion and areas of further research. The summary covers chapter 2 to 5 excluding chapter 1 and 7 that respectively presents the introduction to this thesis and estimation codes for replication purpose.

6.2 Replication of Hartwig's (2008) (Chapter 2)

The plethora of empirical studies on income determinant of health spending motivates me to examine the non-income factors to explain the growth in healthcare spending across countries. Also, the lack of established theory to explain the growth using either income or non-income factors prompted my choice to revisit Baumol (1967) model of "unbalanced growth". This is done by first replicating the most cited study in this area, Hartwig (2008. HW employed Barros (1998) model to test that wage increases in excess of labour productivity growth (i.e. Baumol's variable) is a significant determinant of healthcare expenditure for a sample 19 OECD countries from the period 1960 to 2005 using standard panel data estimators.

I replicated HW's split and un-split models using the same original dataset but different econometric package (Stata 14.1 instead of Eviews). HW's split model regress HCE on real wages per employee, real GDP, and total employment. The un-split model merged the regressors in the split model as a Baumol's variable. HW's provided strong supports for the BCD after estimating the un-split model that was incorrectly justified and derived from the split panel model using a set of coefficient restrictions.

The estimates from my replicated models are very similar to HW but the standard errors and t-statistics are substantially different and this might be due to the way degree of freedom is calculated between Stata and Eviews. However, further robustness checks revealed that the variables and the extracted residuals from the models in the pure replication are not cross-sectionally independent. Outcomes from the first set of diagnostic tests revealed that the standard panel data estimators employed by HW are not robust in the presence of cross-sectional dependence. Also, test of slope homogeneity using the random coefficient model indicated that the relationship HCE and Baumol's variable is heterogeneous. The second set of my robustness checks accommodated the identified problems of cross-sectional dependence, slope heterogeneity and non-stationarity using recently developed panel data estimators (CCEMG and AMG). These estimators produced estimates of the effect of wage-labour productivity gap growth on HCE per capita growth that were smaller in magnitude than those found by HW.

Lastly, after testing the right set of coefficient restrictions, I found that it is wrong in all the considered model cases to combine wages, productivity and labour as a single Baumol variable i.e. aggregating the split model to derive the un-split model. However, Chapter 2 concludes that the Baumol's effect in the health sector is smaller in magnitude than HW's estimates and the empirical model used by HW is not theoretically motivated using key Baumol's Cost Disease axioms. Despite the theoretical gap identified in HW's study and later addressed in Chapter 3, there are still some areas that require further research. This includes the use of GMM based common correlated effect (CCE) mean-group estimator developed by Neal (2015a, b) to account for endogeneity that might arise due to the effect of output shock on Baumol variable through wages and productivity as noted in Bates and Santerre (2013).

6.3 Theoretical Modelling and Testing of Baumol's Cost Disease (Chapter 3)

The lack of strong theoretical framework to Hartwig's (2008) empirical analysis motivates this chapter to develop models that directly test the key BCD hypotheses using observable variables. The derived empirical models incorporates the underlying Baumol

(1967) axioms and properties. The two empirically testable hypotheses examines the effect of economy-wide productivity on the share of labour employed in the health sector and the ratio of health to non-health price index. Also, I extended the derived models to control for age and gender composition of the population, health outcomes (life expectancy at birth and infant mortality), health-related behaviour (tobacco and alcohol consumption per capita), and economic growth.

For the empirical test, the data for the period of 1995 – 2013 for 27 OECD countries were fitted using pooled and mean-group type estimators. For the two BCD hypotheses, estimates from the pooled OLS and two-way fixed effect show strong support for BCD but when fixed effect and country-specific time trends are incorporated into the analyses, the support for Baumol's positions disappear as productivity estimates become negative and statistically insignificant. The inconsistent outcomes serves as motivation to perform additional post-estimation robustness checks such as Ramsey's specification error test, joint significance test of country and time effects, and Bayesian Information Criteria (BIC) least value. The test outcomes revealed that the model with heterogeneous trend is the most preferred specification to test the BCD hypotheses. Also, additional diagnostic test indicated that there is issue of cross-sectional dependence and non-stationarity, and evidence from addressing the issues through the use of heterogeneous panel data estimators did not change the outcome. The chapter concludes that there is no significant relationship to support the BCD predictions for OECD countries. This may be due to the failure of the BCD model for "non-progressive" sectors like health care to account for technology improvements and the resulting substitutability of capital for labour inputs.

However, one of the key areas for further research is the use of dynamic model to test the BCD predictions for the health sector. This includes the use of robust panel data estimator such as GMM based CCE by Neal (2015a, 2015b) to capture the endogeneity that can emanate from price and labour supply shocks effect on productivity in the health sector due to technological changes. Lastly, future study should extend the dataset to cover more period and countries in order to have a more balanced panel data. The identified areas of further research in this chapter will provide more validity and generalisation (or otherwise) to the reported outcomes.

6.4 Monte Carlo Simulation Experiments of Heterogeneous Panel Data Estimators (Chapter 4)

In previous chapters, it was shown that most of the variables used in modelling the economic relationship suffer from three major issues, cross-sectional dependence, non-stationarity and non-homogeneity of slope. Failure to address the issues in estimation might results to highly biased policy inference and the use of standard panel data estimators when they exist can make the estimates inconsistent and biased. This motivates this chapter to test the performance of the pooled type estimators in the presence of the highlighted econometric issues including endogeneity induced by common unobservable factors. Then, I compared the outcomes with the performance metrics of the recently developed panel data estimators designed to accommodate those problems.

The simulation set-ups used in chapter 4 was similar to the DGP used in Bond and Eberhardt (2013b). Two sets of experiments were conducted. The first simulation replicates the experiments in B&E (2013) using the same Monte Carlo DGP (i.e. simulated dataset) set-ups. It then extends the analysis to incorporate additional performance metrics -(RMSE and coverage rate)- for comparing the pooled type (POLS, 2WFE, CCEP, FE, and FD-OLS) estimators relative to the mean-group (MG, CCEMG and AMG) methods. The second experiment specifically replicates the first simulation for three sets of panel data dimensions that were used in chapter 5. For each of the experiment set-up, I considered four different implementation cases, baseline model, heterogeneous linear trends, feedback effect, and beta clubs. However, the overall results indicated that CCEMG is the “best” estimator assessed based on biasness, efficiency and coverage rate. Also, the AMG estimator is relatively good but less robust in addressing endogeneity issue. But, the pooled type estimators, POLS and 2WFE are found to be least biased. The simulation experiment outcomes guided the choice of estimation methods used in examining the income elasticity of healthcare expenditures in chapter 5.

6.5 Income Elasticity of Health Expenditures Analyses using an African Dataset (Chapter 5)

The dearth of empirical studies on income elasticity of health expenditure for African countries motivate the analyses in chapter 5. In testing whether health is a "luxury" or a "necessity" good in Africa, I employed disaggregated and aggregated approaches using the dependent variable, set of regressors, sampled countries, and estimation methods. The income and non-income factors incorporated in the empirical model are selected from previous studies for developing countries. The baseline model regress healthcare expenditure per capita on real GDP per capita, life expectancy, infant mortality rate, share of population under 15 and above 65, per capita net official development assistance, government expenditure as a share of GDP, and heterogeneous liner trends. The total healthcare spending was decomposed into government and out-of-pocket health expenditure. For the baseline analysis, 47 African countries were sampled for the period from 1995 to 2014.

The pre-estimation diagnostic test results revealed that most of the considered variables are non-stationary and cross-sectionally dependent. Estimates from the CCEMG indicated that real income per capita has significant and positive effect on total, government and out-of-pocket expenditures with coefficients of 0.582, 1.375, and 1.131 respectively. But, plots of the confidence interval values for each of the elasticity coefficient clearly showed that they are less than one. This indicates that health is a "necessity" good in Africa. Further robustness checks yield consistent income elasticity coefficients for all the considered cases.

However, to further generalise the empirical outcomes, there is need for further research. First, more robust estimation method such as GMM based common correlated effect (CCE) estimator developed by Neal (2015a, 2015b) need to be implemented to address endogeneity emanating from the simultaneous relationship among GDP, LEX, INM and GFC. Health expenditure can impact health outcomes (LEX and INM) through productivity, and vice-versa. The Monte Carlo simulation experiments by Neal (2015a, 2015b) revealed that the GMM based CCE method is more robust to endogenous regressors in both static and dynamic panel data models. Also, additional data points across more countries is required to have sufficient observations to be able to implement dynamic panel model and the cointegration technique developed by Gengenbach, Urbain, et al. (2009)..

Chapter 7: Presentation and Description of Estimation Codes

Chapter Seven

7.1 Introduction

The econometric packages used in this thesis are: E-Views 8, Stata 14.1 and GAUSS (9 and 16). The codes provided by Hartwig (2008) in E-Views were replicated in Stata for consistency checks and flexibility to perform more rigorous robustness tests in Chapter 2. The tests of the designed BCD hypotheses were performed using Stata 14.1 in Chapter 3. The simulation experiments in Chapter 4 were conducted using GAUSS version 9 and 16. The original replication commands provided by Bond and Eberhardt (2013) were written using GAUSS 9.0. I replaced obsolete commands to enable implementation in version 16 and also wrote additional diagnostic programmes. The original and modified codes are presented in section 6.4. Lastly, Chapter 5 that investigates the income elasticity of health care spending used Stata 14.1.

7.2 Replication of Hartwig (2008b)

```
//Change the .ado file directory to my P drive
sysdir set OLDPLACE "P:\Desktop\ado"

sysdir set PLUS "P:\Desktop\ado\plus"

use "\\file\UsersA$\aaa121\Home\Desktop\Stata\hartwig.dta"

xtset cid year

summarize dlhcep dlwspe dlgdpr dlemp dlprod baumolv

by country, sort: summarize dlhcep dlwspe dlgdpr dlemp dlprod baumolv

//'Baumol variable ' split
// Pooled OLS
reg dlhcep dlwspe dlgdpr dlemp, vce(cluster cid)

// Cross-section R.E
xtreg dlhcep dlwspe dlgdpr dlemp, re sa vce(cluster cid)

// Time Period R.E
xtreg dlhcep dlwspe dlgdpr dlemp i.year, re sa vce(cluster cid)


//'Baumol variable ' Unsplit
// Pooled OLS
reg dlhcep baumolv, vce(cluster cid)

// Cross-section R.E
xtreg dlhcep baumolv, re sa vce(cluster cid)
```

```
// Time Period R.E
xtreg dlhcep baumolv i.year, re sa vce(cluster cid)


//**Robustness Check #1 ***//
///*************Panel Time Series Cross-sectional dependence TesT*******
xtcd dlhcep dlwspe dlgdpr dlemp dlprod baumolv



////***********Estimated Residual Cross-sectional dependence Tests
***********
qui: xtreg dlhcep dlwspe dlgdpr dlemp, re sa vce(cluster cid)
xtcsd, pesaran abs
xtcsd, friedman abs
xtcsd, frees abs

qui: xtreg dlhcep dlwspe dlgdpr dlemp i.year, re sa vce(cluster cid)
xtcsd, pesaran abs
xtcsd, friedman abs
xtcsd, frees abs

qui: xtreg dlhcep baumolv, re sa vce(cluster cid)
xtcsd, pesaran abs
xtcsd, friedman abs
xtcsd, frees abs

qui: xtreg dlhcep baumolv i.year, re sa vce(cluster cid)
xtcsd, pesaran abs
xtcsd, friedman abs
xtcsd, frees abs


//**Robustness Check #2 ***//
//'Baumol variable ' split
//RCM
xtrc dlhcep dlwspe dlgdpr dlemp, vce(conventional)

//MG
xtmg dlhcep dlwspe dlgdpr dlemp, robust res(sp1)
xtmg dlhcep dlwspe dlgdpr dlemp, trend robust res(sp2)

//CCEMG
xtmg dlhcep dlwspe dlgdpr dlemp, cce robust res(sp3)
xtmg dlhcep dlwspe dlgdpr dlemp, cce trend robust res(sp4)


//AMG
xtmg dlhcep dlwspe dlgdpr dlemp, aug robust res(sp5)
xtmg dlhcep dlwspe dlgdpr dlemp, aug trend robust res(sp6)


xtcd sp1 sp2 sp3 sp4 sp5 sp6



//'Baumol variable ' Unsplit
//RCM
xtrc dlhcep baumolv, vce(conventional)
```

```
//MG
xtmg dlhcep baumolv, robust res(up1)
xtmg dlhcep baumolv, trend robust res(up2)

//CCEMG
xtmg dlhcep baumolv, cce robust res(up3)
xtmg dlhcep baumolv, cce trend robust res(up4)


//AMG
xtmg dlhcep baumolv, aug robust res(up5)
xtmg dlhcep baumolv, aug trend robust res(up6)


xtcd up1 up2 up3 up4 up5 up6




///Robustness #3
//Wald Parameters Restriction Test
qui: reg dlhcep dlwspe dlgdpr dlemp, vce(cluster cid)
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1

qui: xtreg dlhcep dlwspe dlgdpr dlemp, re sa vce(cluster cid)
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1

qui: xtreg dlhcep dlwspe dlgdpr dlemp i.year, re sa vce(cluster cid)
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1


qui: xtrc dlhcep dlwspe dlgdpr dlemp, vce(conventional)
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1

qui: xtmg dlhcep dlwspe dlgdpr dlemp, robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1

qui: xtmg dlhcep dlwspe dlgdpr dlemp, trend robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1


qui: xtmg dlhcep dlwspe dlgdpr dlemp, cce robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1

qui: xtmg dlhcep dlwspe dlgdpr dlemp, cce trend robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1



qui: xtmg dlhcep dlwspe dlgdpr dlemp, aug robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1
```

```
qui: xtmg dlhcep dlwspe dlgdpr dlemp, aug trend robust
test dlwspe - dlgdpr + dlemp = 0
test dlwspe - dlgdpr + dlemp = 1


qui: reg dlhcep baumolv, vce(cluster cid)
test baumolv = 0
test baumolv = 1

qui: xtreg dlhcep baumolv, re sa vce(cluster cid)
test baumolv = 0
test baumolv = 1

qui: xtreg dlhcep baumolv i.year, re sa vce(cluster cid)
test baumolv = 0
test baumolv = 1

qui: xtrc dlhcep baumolv, vce(conventional)
test baumolv = 0
test baumolv = 1

qui: xtmg dlhcep baumolv, robust
test baumolv = 0
test baumolv = 1

qui: xtmg dlhcep baumolv, trend robust
test baumolv = 0
test baumolv = 1

qui: xtmg dlhcep baumolv, cce robust
test baumolv = 0
test baumolv = 1

qui: xtmg dlhcep baumolv, cce trend robust
test baumolv = 0
test baumolv = 1


qui: xtmg dlhcep baumolv, aug robust
test baumolv = 0
test baumolv = 1

qui: xtmg dlhcep baumolv, aug trend robust
test baumolv = 0
test baumolv = 1
```

GRAPHS

```
clear
use "\\file\UsersA$\aaa121\Home\Desktop\Stata\average values by cross-
section.dta"
label var dlhcep "Av. HCE Per Capita Growth"
label var dlwspe " Av. Wages Per Employee Growth"
label var baumol "Av. Wage-Productivity Gap Growth"
label var dlgdpr "Av. Real GDP Growth"
label var dlprod "Av. Productivity Per Employee Growth"


//Figure 2.1
gen pos=3
```

```
replace pos = 9 if country == "Iceland"
replace pos = 9 if country == "Austria"
replace pos = 12 if country == "Italy"
replace pos = 8 if country == "Germany"
replace pos = 3 if country == "UK"
replace pos = 9 if country == "Finland"
replace pos = 12 if country == "France"
replace pos = 9 if country == "USA"

graph twoway (lfitci dlhcep baumol) (scatter dlhcep baumol, mlabel(country)
mlabv(pos)), title("HCE per capita Growth by Baumol variable") ytitle("HCE
Per Capita Growth Rate") xtitle("Wage-Productivity Gap Growth Rate")
legend(ring(0) pos(5) order(2 "linear fit" 1 "95% CI")) note("Data Source:
Hartwig, 2008")

//Figure 2.2A
clear
use "\\file\UsersA$\aaa121\Home\Desktop\Stata\hartwig.dta"
twoway (line dlhcep year) (line dlwspe year, yaxis(2)), by(country)

//Figure 2.3A
twoway (line dlhcep year) (line baumolv year, yaxis(2)), by(country)


//Figure 2.4
clear
use "\\file\UsersA$\aaa121\Home\Desktop\Stata\average values by cross-
section.dta"
label var dlhcep "Av. HCE Per Capita Growth"
label var dlwspe " Av. Wages Per Employee Growth"
label var baumol "Av. Wage-Productivity Gap Growth"
label var dlgdpr "Av. Real GDP Growth"
label var dlprod "Av. Productivity Per Employee Growth"
graph matrix dlhcep dlwspe dlgdpr dlprod baumol, maxes(ylab(#5, grid)
xlab(#5, grid))


clear
use "\\file\UsersA$\aaa121\Home\Desktop\Stata\heterogeneous slope.dta"
drop pos
//Figure 2.5
gen pos=3
replace pos = 6 if country == "Iceland"
replace pos = 12 if country == "Ireland"
replace pos = 9 if country == "Austria"
replace pos = 12 if country == "Italy"
replace pos = 8 if country == "Germany"
replace pos = 3 if country == "UK"
replace pos = 9 if country == "Finland"
replace pos = 12 if country == "France"
replace pos = 9 if country == "USA"
graph twoway (scatter rcm sample, mlabel(country) mlabv(pos)),
title("Effect of Baumol's Variable on HCE Per Capita Growth")
subtitle("Heterogeneous Effect Size across OECD Countries") ytitle("Effect
Size") xtitle("Sample") legend(ring(0) pos(5) order(2 "linear fit" 1 "95%
CI")) note("Source: Estimates from Random Coefficients Model")
//Figure 2.6
drop pos
gen pos=3
replace pos = 3 if country == "Iceland"
replace pos = 9 if country == "Ireland"
```

```
replace pos = 9 if country == "Austria"
replace pos = 12 if country == "Italy"
replace pos = 6 if country == "Germany"
replace pos = 12 if country == "Denmark"
replace pos = 12 if country == "South Korea"
replace pos = 3 if country == "UK"
replace pos = 6 if country == "Finland"
replace pos = 12 if country == "France"
replace pos = 9 if country == "USA"
graph twoway (scatter mg sample, mlabel(country) mlabv(pos)), title("Effect
of Baumol's Variable on HCE Per Capita Growth") subtitle("Heterogeneous
Effect Size across OECD Countries") ytitle("Effect Size") xtitle("Sample")
legend(ring(0) pos(5) order(2 "linear fit" 1 "95% CI")) note("Source:
Estimates from Mean Group Panel Model")



//Figure 2.7
drop pos
gen pos=3
replace pos = 3 if country == "Iceland"
replace pos = 9 if country == "Ireland"
replace pos = 9 if country == "Austria"
replace pos = 3 if country == "Italy"
replace pos = 3 if country == "Germany"
replace pos = 3 if country == "Denmark"
replace pos = 3 if country == "South Korea"
replace pos = 3 if country == "UK"
replace pos = 9 if country == "Switzerland"
replace pos = 3 if country == "Finland"
replace pos = 12 if country == "France"
replace pos = 12 if country == "USA"
graph twoway (scatter ccemg sample, mlabel(country) mlabv(pos)),
title("Effect of Baumol's Variable on HCE Per Capita Growth")
subtitle("Heterogeneous Effect Size across OECD Countries") ytitle("Effect
Size") xtitle("Sample") legend(ring(0) pos(5) order(2 "linear fit" 1 "95%
CI")) note("Source: Estimates from Common Correlated Effect Mean Group
(CCEMG) Panel Model")


//Figure 2.8
drop pos
gen pos=3
replace pos = 3 if country == "Iceland"
replace pos = 9 if country == "Ireland"
replace pos = 9 if country == "Austria"
replace pos = 3 if country == "Italy"
replace pos = 3 if country == "Germany"
replace pos = 3 if country == "Denmark"
replace pos = 3 if country == "South Korea"
replace pos = 3 if country == "UK"
replace pos = 9 if country == "Switzerland"
replace pos = 3 if country == "Finland"
replace pos = 12 if country == "France"
replace pos = 12 if country == "USA"
graph twoway (scatter amg sample, mlabel(country) mlabv(pos)),
title("Effect of Baumol's Variable on HCE Per Capita Growth")
subtitle("Heterogeneous Effect Size across OECD Countries") ytitle("Effect
Size") xtitle("Sample") legend(ring(0) pos(5) order(2 "linear fit" 1 "95%
CI")) note("Source: Estimates from Augmented Mean Group (AMG) Panel Model")
```

```
//Figure 2.9
clear
use "\\file\UsersA$\aaa121\Home\Desktop\Stata\effect size by estimator.dta"
graph hbar est, over( models, axis(off) sort(1) ) blabel(group, pos(base)
color(bg)) ytitle( "Average Cross-sectional Effect Size" ) title("Baumol's
Effect Size in OECD by Estimators")
```

7.3 Test of BCD Hypotheses

```
clear
//Change the .ado file directory to my P drive
sysdir set OLDPLACE "P:\Desktop\ado"

sysdir set PLUS "P:\Desktop\ado\plus"

use
"\\file\UsersA$\aaa121\Home\Desktop\Stata\BCD\BCD_Dataset_PHN_LHSL_27_count
ries_29-02-2016.dta"

ge phpnh = 100*phn

ge lhl = 100*lhsl


summ phpnh lhl prod pop14 pop65 male lex infmo tobaco alcohc gdpg
replace lhl = log(lhl)

xtset cid year

////Panel Series CD Test
xtcd lhl phpnh prod
xtcd pop14 pop65 male gdpg
xtcd llex linfmo lalcohc


//////////////Maddala & Wu (1999) & Pesaran (2007) [CIPS] Panel Unit Root
test/////////////
///Levels
multipurt lhl phpnh lprod, lags(1)
multipurt pop14 pop65 male gdpg, lags(1)
multipurt llex linfmo, lags(1)
multipurt ltobaco, lags(1)
multipurt lalcohc, lags(1)

///First Difference
////Genereate First Difference Series/////
gen dlhl = d.lhl
gen dphpnh = d.phpnh
gen dlprod = d.lprod
gen dpop14 = d.pop14
gen dpop65 = d.pop65
gen dmale = d.male
gen dgdpg= d.gdpg
gen dllex = d.llex
gen dlinfmo = d.linfmo
gen dltobaco = d.ltobaco
gen dlalcohc = d.lalcohc

multipurt dlhl dphpnh dlprod, lags(1)
```

```
multipurt dpop14 dpop65 dmale dgdpg, lags(1)
multipurt dllex dlinfmo, lags(1)
multipurt dltobaco, lags(1)
multipurt dlalcohc, lags(1)


//For LHL models 1-9//
reg lhl lprod pop14 pop65 male llex linfmo
predict le1, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc
predict le2, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg
predict le3, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo  i.year i.cid
predict le4, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc  i.year i.cid
predict le5, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg i.year
i.cid
predict le6, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo cid##c.year
predict le7, residuals
estat ic
estat ovtest


reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc cid##c.year
predict le8, residuals
estat ic
estat ovtest

reg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg cid##c.year
predict le9, residuals
estat ic
estat ovtest
estat ovtest

//CROSS-SECTION DEPENDENCE & PURT TEST//
//For the Predicted Residuals//

xtcd le1 le4 le7

multipurt le1 le4 le7, lags(1)
```

```
//For PHPNH models 1-9//
reg phpnh prod pop14 pop65 male lex infmo
predict pe1, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc
predict pe2, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg
predict pe3, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo  i.year i.cid
predict pe4, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc  i.year i.cid
predict pe5, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg i.year i.cid
predict pe6, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo cid##c.year
predict pe7, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc cid##c.year
predict pe8, residuals
estat ic
estat ovtest

reg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg cid##c.year
predict pe9, residuals
estat ic
estat ovtest


//CROSS-SECTION DEPENDENCE & PURT TEST//
//For the Predicted Residuals//

xtcd pe1 pe4 pe7

multipurt pe1 pe4 pe7, lags(1)


///*******TEST OF SERIAL CORRELATION********////
tabulate cid, gen(cid)
forvalues i = 1/27 {
                gen cidyear`i' = cid`i'*year
}
```

```
//**LHL Model 7**//
xtserial lhl lprod pop14 pop65 male llex linfmo cid1-cid27 year cidyear1-
cidyear27
//**LHL Model 8**//
xtserial lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc cid1-cid27
year cidyear1-cidyear27
//**LHL Model 9**//
xtserial lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg cid1-
cid27 year cidyear1-cidyear27


//**PHN Model 7**//
xtserial phpnh prod pop14 pop65 male lex infmo cid1-cid27 year cidyear1-
cidyear27
//**PHN Model 8**//
xtserial phpnh prod pop14 pop65 male lex infmo tobaco alcohc cid1-cid27
year cidyear1-cidyear27
//**PHN Model 9**//
xtserial phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg cid1-
cid27 year cidyear1-cidyear27


//PCSE:- LHL Model 7//
xtpcse lhl lprod pop14 pop65 male llex linfmo cid1-cid27 year cidyear1-
cidyear27, correlation(ar1)
ereturn list
di e(r2_a)
di e(rmse)

//Heterogeneous Slopes Estimators with Group-Specific Trends//
//LHL Model 7//
xtmg lhl lprod pop14 pop65 male llex linfmo, trend res(let1)
xtmg lhl lprod pop14 pop65 male llex linfmo, cce trend res(let2)
xtmg lhl lprod pop14 pop65 male llex linfmo, aug trend res(let3)

//LHL Model 8//
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc, trend
res(let4)
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc, cce trend
res(let5)
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc, aug trend
res(let6)

//LHL Model 9//
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg, trend
res(let7)
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg, cce trend
res(let8)
xtmg lhl lprod pop14 pop65 male llex linfmo ltobaco lalcohc gdpg, aug trend
res(let9)

//PCSE:- PHPNH Model 7//
xtpcse phpnh prod pop14 pop65 male lex infmo cid1-cid27 year cidyear1-
cidyear27, correlation(ar1)
ereturn list
di e(r2_a)
di e(rmse)

//PHPNH Model 7//
xtmg phpnh prod pop14 pop65 male lex infmo, trend res(pet1)
xtmg phpnh prod pop14 pop65 male lex infmo, cce trend res(pet2)
```

```
xtmg phpnh prod pop14 pop65 male lex infmo, aug trend res(pet3)

//PHPNH Model 8//
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc, trend res(pet4)
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc, cce trend
res(pet5)
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc, aug trend
res(pet6)

//PHPNH Model 9//
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg, trend
res(pet7)
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg, cce trend
res(pet8)
xtmg phpnh prod pop14 pop65 male lex infmo tobaco alcohc gdpg, aug trend
res(pet9)

//END OF Heterogeneous Slopes Estimation for MG, CCEMG and AMG//


//RESIDUAL CROSS_SECTION DEPENDENCE TEST//
xtcd let1 let2 let3
xtcd let4 let5 let6
xtcd let7 let8 let9


xtcd pet1 pet2 pet3
xtcd pet4 pet5 pet6
xtcd pet7 pet8 pet9

///////Residual Based Cointegration Technique///////
multipurt let1 let2 let3, lags(1)
multipurt let4 let5 let6, lags(1)
multipurt let7 let8 let9, lags(1)

multipurt pet1 pet2 pet3, lags(1)
multipurt pet4 pet5 pet6, lags(1)
multipurt pet7 pet8 pet9, lags(1)
```

7.4 Monte Carlo Simulation Experiments

```
/*********************************************
**                                          **
**    Monte Carlo Program                     **
**                                          **
**  MC 2e                                   **
**                                          **
**  (a) Nonstationary variables             **
**  (b) common f's                          **
**  (c) factor overlap btw x & y            **
**  (d) loadings on f's are heterog         **
**  (e) heterog parameters on x in y        **
**  (f) RMSE, Coverage & Efficiency Rates   **
**                                          **
**  24th April 2016                         **
**                                          **♣
*********************************************/
new;
cls;
t0 = date;
```

```
"*************************************************************************";
"MC2(e) simulated on: "  datestr(0) "  at   "  timestr(0);
"Case: heterog beta, common factors with heterog loadings, ";
"      overlap of factors btw x & y";
"*************************************************************************";

/******************
*   Replications   *
******************/
iter    = 5000;       @ # of iterations @
MC2edat   = zeros(iter,1);    /* storage of final results */
/***********************************************************************
*******************/
/**********************
*   Panel dimensions  *
**********************/

/* Time-series dimension */
let jj[6,1]= 10 20 30 50 100 150;
for j1(2,2,1);
    jj1=jj[j1,1];
    /* Cross-section dimension */

    let jjj[6,1]= 10 20 30 50 100 150;
    for j2(3,3,1);
        jj2=jjj[j2,1];
        /****************
        *   Paramaeters  *
        ****************/
        /* Variation in beta (no/yes) */

        let jjjj[2,1]= 0 1;
        for j3(2,2,1);
            jj3=jjjj[j3,1];
            /* Drift/intercept in the f-equation (no/yes) */
            /* note: f's might be 'turned off' below! */

            let jjjjj[2,1]= 0 1;
            for j4(2,2,1);
                jj4=jjjjj[j4,1];
                /* Variation in the unobserved f in the y-equation (no/yes)
*/
                /* note: f's might be 'turned off' below! */

                let jjjjjj[2,1]= 0 1;
                for j5(2,2,1);
                    jj5=jjjjjj[j5,1];
                    /* Linear trend in the y-equation (no/yes) */

                    let jjjjjjj[2,1]= 0 1;
                    for j6(1,1,1);
                        jj6=jjjjjjj[j6,1];
                        /* Recap of other parameter and iteration values */
                        tt      = jj1;      @ # of T observations @
                        nn      = jj2;      @ # of N observations @
                        betac    = 1;        @ coefficient on x (mean) @
                        seed    = 1974;
                        /* Pesaran setup: factors are nonstationary */
                        rho_1=1;
                        rho_2=1;
                        rho_3=1;
```

```
                        /* Factor loadings on common observed effect
(intercepts in y- and x-equations (fixed) */
                        {alpha_i,seed}=rndu(nn,1,seed);
                        alpha_i=2.5 + (alpha_i-1);
                        {a_i,seed}=rndu(nn,1,seed);
                        a_i=6+ 2 .* (a_i-1);
                        /*the drift terms in the unobserved common factor
equation */
                        mu_1=0.015;      /* baseline value: 0.015 */
                        mu_2=0.012;      /* baseline value: 0.012 */
                        mu_3=0.01;       /* baseline value: 0.01 */
                        /*the factor loadings (means) on the unobserved f's
in the x- and y-equations */
                        /* Note: these might be 'turned off' in the
construction of heterogeneous loadings below */
                        gamma_y1=0.5;   /* baseline value: 0.5, thus range
in theory [0, 1] */
                        gamma_y2=0.75;  /* baseline value: 0.75, thus range
in theory [0.25, 1.25] */
                        gamma_x1=0.5;   /* baseline value: 0.5, thus range
in theory [0, 1]  */
                        gamma_x3=0.75;  /* baseline value: 0.75, thus range
in theory [0.25, 1.25]   */

                        /* parameter on the simultaneity/feedback term */
                        gamma_eps=0;  /* baseline value: 0, no
simultaneity/feedbacks */
                        /* autoregressive component of the x-equation
errors */
                        ar_x=0.25;       /* baseline: 0.25 */
                        /* autoregressive component of the y-equation
errors */
                        ar_eps=0;       /* Baseline: 0 - cointegration, no
AR */

/***************************************************************************
*******************/
                        /**************************************
                        *   Storage-vectors for the estimates *
                        **************************************/
                        /* Technology parameters in the y-equation */
                        alphaM  = zeros(iter,1); /* TFP level */
                        betaM   = zeros(iter,1); /* capital coefficient */
                        /* THE POOLED REGRESSIONS */
                        /* POLS estimator (year-dummy augmented)*/
                        olsb    = zeros(iter,1) ;
                        olsst   = zeros(iter,1);
                        olst    = zeros(iter,1);
                        /* Fixed effects estimator (year-dummy augmented)*/
                        feb    = zeros(iter,1) ;
                        fest   = zeros(iter,1);
                        fet    = zeros(iter,1);
                        /* CCEP*/
                        cceb    = zeros(iter,1) ;
                        ccest   = zeros(iter,1);
                        ccet    = zeros(iter,1);
                        /* First difference OLS */
                        fdb    = zeros(iter,1) ;
                        fdst   = zeros(iter,1) ;
                        fdt     = zeros(iter,1) ;
                        /* Infeasible Pooled */
```

```
inffeb    = zeros(iter,1) ;
inffest   = zeros(iter,1) ;
inffet    = zeros(iter,1) ;

/* THE AVERAGED COUNTRY REGRESSIONS */
/* CCEMG */
ccemgb  = zeros(iter,1) ;
ccemgst = zeros(iter,1) ;
ccemgt  = zeros(iter,1) ;
/* AMG (i) & (ii)*/
amgb = zeros(iter,1);
amgst = zeros(iter,1) ;
amgt = zeros(iter,1) ;
amg2b = zeros(iter,1);
amg2st = zeros(iter,1) ;
amg2t = zeros(iter,1) ;
/* Naive MG */
mgb = zeros(iter,1);
mgst = zeros(iter,1) ;
mgt = zeros(iter,1) ;
/* Infeasible MG */
infmgb = zeros(iter,1);
infmgst = zeros(iter,1) ;
infmgt = zeros(iter,1) ;

/********************
*    STORAGE: RMSE   *
********************/
mseols=zeros(iter,1);
msefe=zeros(iter,1);
msecce=zeros(iter,1);
msefd=zeros(iter,1);
mseinffe=zeros(iter,1);
mseccemg=zeros(iter,1);
mseamg=zeros(iter,1);
mseamg2=zeros(iter,1);
msemg=zeros(iter,1);
mseinfmg=zeros(iter,1);

/********************
*    STORAGE: Coverage   *
********************/
cintols=zeros(iter,1);
cintfe=zeros(iter,1);
cintcce=zeros(iter,1);
cintfd=zeros(iter,1);
cintinffe=zeros(iter,1);
cintccemg=zeros(iter,1);
cintamg=zeros(iter,1);
cintamg2=zeros(iter,1);
cintmg=zeros(iter,1);
cintinfmg=zeros(iter,1);

cuols=zeros(iter,1);
cufe=zeros(iter,1);
cucce=zeros(iter,1);
cufd=zeros(iter,1);
cuinffe=zeros(iter,1);
cuccemg=zeros(iter,1);
cuamg=zeros(iter,1);
cuamg2=zeros(iter,1);
```

```
                        cumg=zeros(iter,1);
                        cuinfmg=zeros(iter,1);

                        clols=zeros(iter,1);
                        clfe=zeros(iter,1);
                        clcce=zeros(iter,1);
                        clfd=zeros(iter,1);
                        clinffe=zeros(iter,1);
                        clccemg=zeros(iter,1);
                        clamg=zeros(iter,1);
                        clamg2=zeros(iter,1);
                        clmg=zeros(iter,1);
                        clinfmg=zeros(iter,1);


/***************************************************************************
********************/
                        /*********************
                        *    OUTPUT: Setup   *
                        *********************/
                        format /rd 2,2;

                        if jj4==1;
                            "Drift in all f-equations";
                        elseif jj4==0;
                            "No drift in the f-equations";
                        endif;

                        if jj5==1;
                            "Common factors have heterogeneous factor
loadings across countries";
                        elseif jj5==0;
                            "Common factors have the same factor loadings
across countries";
                        endif;

                        format /rd 2,2;
                        "Autoregressive errors in x: ar_u coefficient "
ar_x;
                        "Feedback coefficient: gamma_eps " gamma_eps;

"*************************************************************************";

/***************************************************************************
********************/
                        /****************************
                        *    ITERATIONS BEGIN HERE   *
                        ****************************/

                        for i(1,iter,1);
                            seed=1974;
                            seed_i=seed+i;
                            seed_i2=seed+i+2;
                            seed_i3=seed+i+3;
                            seed_i4=seed+i+4;
                            seed_i5=seed+i+5;
                            seed_i6=seed+i+6;
                            seed_i7=seed+i+i;
                            /***********************************
                            *   Observed common factors (d)     *
                            ***********************************/
```

```
                            /* intercepts in x- & y-equations */
                            d_t=ones(tt+50,1);
                            /*************************************
                            *   Unobserved common factors (f)     *
                            *************************************/
                            f_1t=zeros(tt+50,1);
                            f_2t=zeros(tt+50,1);
                            f_3t=zeros(tt+50,1);
                            seed_i=seed+i;
                            {v_ft1,seed_i}=rndn(tt+50,1,seed_i);
                            v_ft1=sqrt(0.00125).*v_ft1;

                            {v_ft2,seed_i2}=rndn(tt+50,1,seed_i2);
                            v_ft2=sqrt(0.00125).*v_ft2;

                            {v_ft3,seed_i3}=rndn(tt+50,1,seed_i3);
                            v_ft3=sqrt(0.00125).*v_ft3;

                            /* benchmark value: 0.00125 */

                            for j(2,tt+50,1);
                                f_1t[j,1]=jj4*mu_1+rho_1*f_1t[j-
1,1]+v_ft1[j,1];
                                f_2t[j,1]=jj4*mu_2+rho_2*f_2t[j-
1,1]+v_ft2[j,1];
                                f_3t[j,1]=jj4*mu_3+rho_3*f_3t[j-
1,1]+v_ft3[j,1];

                            endfor;
                            f_1tlag=zeros(1,1)|f_1t[1:rows(f_1t)-1,.];
                            f_2tlag=zeros(1,1)|f_2t[1:rows(f_2t)-1,.];
                            f_3tlag=zeros(1,1)|f_3t[1:rows(f_3t)-1,.];

                            /* Result: 3 unobserved common factors f_1t,
f_2t, f_3t */

/*******************************************************
                            *    Errors in the x equation (vary across
countries i)  *

*******************************************************/
                            u_it=zeros(tt+50,nn);
                            {v_sig,seed_i2}=rndu(nn,1,seed_i2);
                            v_sig=2+ 2 .*(v_sig -0.5);
                            v_sig=v_sig ./ 1000; /* benchmark: ./ 1000 */
                            {vt,seed_i3}=rndn(tt+50,1,seed_i3);

                            for j(1,nn,1);
                                u_it[.,j]=sqrt(v_sig[j,1]).* vt;

                            endfor;
                            /* variance ranges from sqrt(0.001) to
sqrt(0.003) */
                            /*  error matrix (tt by n)  */

/************************************************
                            *    Factor loadings of observed common effects
*

************************************************/
```

```
                              /* alpha_i & a_i are fixed across replications
--- see above */

/**********************************************************************
                              *   Parameters on the unobserved common factor
in the y equation      *

**********************************************************************/

                              {gamma_y1i,seed_i5}=rndu(nn,1,seed_i5);
                              gamma_y1i=gamma_y1+jj5*(gamma_y1i -0.5);

                              {gamma_y2i,seed_i4}=rndu(nn,1,seed_i4);
                              gamma_y2i=gamma_y2+jj5*(gamma_y2i -0.5);

                              {gamma_x1i,seed_i6}=rndu(nn,1,seed_i6);
                              gamma_x1i=gamma_x1+jj5*(gamma_x1i -0.5);

                              {gamma_x3i,seed_i7}=rndu(nn,1,seed_i7);
                              gamma_x3i=gamma_x3+jj5*(gamma_x3i -0.5);


                              /* Factor loadings on lagged factors: rho *
gamma_xi */
                              gamma_x1ilag=ar_x .* gamma_x1i;
                              gamma_x3ilag=ar_x .* gamma_x3i;

                              /*
                              No common factors
                              gamma_y1i=0*(rndus(nn,1,seed_i5)-0.5);
                              gamma_y2i=0*(rndus(nn,1,seed_i4)-0.5);
                              gamma_x1i=0*(rndus(nn,1,seed_i6)-0.5);
                              gamma_x3i=0*(rndus(nn,1,seed_i2)-0.5);

                              Common factors, but no overlap btw x and y:
                              gamma_y1i=0*(rndus(nn,1,seed_i5)-0.5);
                              gamma_y2i=gamma_y2+(rndus(nn,1,seed_i4)-0.5);
                              gamma_x1i=0*(rndus(nn,1,seed_i6)-0.5);
                              gamma_x3i=gamma_x3+(rndus(nn,1,seed_i2)-0.5);

                              Factor overlap:
                              gamma_y1i=gamma_y1+jj5*(rndus(nn,1,seed_i5)-
0.5);
                              gamma_y2i=gamma_y2+jj5*(rndus(nn,1,seed_i4)-
0.5);


                              gamma_x1i=gamma_x1+jj5*(rndus(nn,1,seed_i6)-
0.5);
                              gamma_x3i=gamma_x3+jj5*(rndus(nn,1,seed_i2)-
0.5);
                              */
                              /***********************
                              *    beta parameters    *
                              ***********************/
                              @ beta_i: either they do not vary (1), or they
uniformly over [0.75, 1.25] with mean 1 @
                              {beta_i,seed_i}=rndu(nn,1,seed_i);
                              beta_i=betac+jj3*((beta_i-0.5)/2);
                              betaM[i,1]=meanc(beta_i);

/**********************************************
```

```
                            *    Errors in the y equation (vary across i)
*

*********************************************/
                            /* benchmark value: 0.00125 */
                            {eps_it,seed_i4}=rndn(tt+50,nn,seed_i4);
                            eps_it=sqrt(.00125).*eps_it;
                            /*  Result: an error matrix (tt by n)  */
                            /* lagged errors (may be used in later
simulations) */


eps2=zeros(1,cols(eps_it))|eps_it[1:rows(eps_it)-1,.];

eps3=zeros(2,cols(eps_it))|eps_it[1:rows(eps_it)-2,.];

                            /***********************
                            *     X and Y series    *
                            ***********************/
                            gammas= zeros(tt+50,nn);
                            y_it=zeros(tt+50,nn);
                            x_it=zeros(tt+50,nn);


                            for k(1,nn,1);
                                for p(2,tt+50,1);
                                    x_it[p,k]=((1-ar_x).*a_i[k,1]) +
(gamma_x1i[k,1]*f_1t[p,1]) - (gamma_x1ilag[k,1] .* f_1tlag[p,1]) +
(gamma_x3i[k,1]*f_3t[p,1]) - (gamma_x3ilag[k,1] .* f_3tlag[p,1]) +
(ar_x.*x_it[p-1,k]) + u_it[p,k];

                                endfor;

                            endfor;

                            for k(1,nn,1);
                                y_it[.,k]=alpha_i[k,1].*(d_t) +
beta_i[k,1].*x_it[.,k] + gamma_y1i[k,1] .* f_1t+ gamma_y2i[k,1] .* f_2t +
eps_it[.,k];

                            endfor;

                            x_it=x_it[51:rows(x_it),.];
                            y_it=y_it[51:rows(y_it),.];
                            f_1t=f_1t[51:rows(f_1t),.];
                            f_2t=f_2t[51:rows(f_2t),.];
                            f_3t=f_3t[51:rows(f_3t),.];
                            f_1tlag=f_1tlag[51:rows(f_1tlag),.];
                            f_2tlag=f_2tlag[51:rows(f_2tlag),.];
                            f_3tlag=f_3tlag[51:rows(f_3tlag),.];
                            eps_it=eps_it[51:rows(eps_it),.];
                            /* Result: x matrix (tt by nn), y matrix (tt by
nn) */
                            /* For the pooled regressions */
                            /****************************/
                            /* Prep OLS and FE */
                            /******************/
ydum=eye(tt);
ydum2=ydum[.,2:cols(ydum)]; /* year dummies */
ydum2=ones(nn,1) .*. ydum2;
cdum=eye(nn);
```

```
cdum=  cdum .*. ones(tt,1); /* country dummies */


/* OLS */
xols=vec(x_it)~ones(tt*nn,1)~ydum2; /* ~ydum2 */
yols=vec(y_it);

/* FE  */
xfe=vec(x_it)~cdum~ydum2;  /* ~ydum2 */
yfe=vec(y_it);


/* Prep CCEP */
/*************/
xxxt=meanc(x_it.');
yyyt=meanc(y_it.');
xc=vec(x_it);
xsec=eye(nn) .*. xxxt;
ysec=eye(nn) .*. yyyt;
xc=xc~ysec~xsec~cdum;
yc=vec(y_it);


/* Prep FD */
/***********/
ydumfd=ydum[2:rows(ydum),2:cols(ydum)]-ydum[1:rows(ydum)-1,2:cols(ydum)];
ydumfd=ones(nn,1) .*. ydumfd;             /* year dummies in first
difference */
dxx1=x_it[2:rows(x_it),.];
dxx2=x_it[1:rows(x_it)-1,.];
dxxx=dxx1-dxx2;
dyy1=y_it[2:rows(y_it),.];
dyy2=y_it[1:rows(y_it)-1,.];
dyyy=dyy1-dyy2;
dx=vec(dxxx);     /* x in FD */
dx=dx~ydumfd;     /* ~ydumfd RHS */
dy=vec(dyyy);     /* y in FD */


/* Prep Infeasible FE */
/*********************/
tfp3=eye(nn) .*. f_1t ~ eye(nn) .*. f_2t;
cdum=eye(nn);
cdum=cdum .*. ones(tt,1);
x=vec(x_it);
y=vec(y_it);
x=x~tfp3~cdum;

/****************************************************************************
*******************/

/**************************
*    ESTIMATION RESULTS    *
**************************/
zstat=cdfNi(0.975);
/* Pooled estimates */

/********************************
*    OLS with T-1 year dummies   *
********************************/
```

```
olsbi = invpd(xols'xols)*(xols'yols);
e  = yols - xols*olsbi;
s2 = (e'e)/(nn*tt-1-(tt-1)-1); /* df = obs - k - (t-1) - intercept */
v  = s2*invpd(xols'xols);
se = sqrt(diag(v));

olsb[i,1]=olsbi[1,1];
olsst[i,1]= se[1,1];
mseols[i,1]=(olsb[i,1]-betaM[i,1])^2;
clols[i,1]=betaM[i,1]-(zstat*olsst[i,1]);
cuols[i,1]=betaM[i,1]+(zstat*olsst[i,1]);
if (clols[i,1] <= olsb[i,1]) AND (olsb[i,1] <= cuols[i,1]);
    cintols[i,1]=1;
endif;
clear se,e,s2,v,xols,olsbi,yols;


/********************************
*    FE with T-1 year dummies   *
********************************/

febi = invpd(xfe'xfe)*(xfe'yfe);
e  = yfe - xfe*febi;
s2 = (e'e)/(nn*tt-1-(tt-1)-nn); /* df = obs - k - (t-1) - N intercepts */
v  = s2*invpd(xfe'xfe);
se = sqrt(diag(v));

feb[i,1]=febi[1,1];
fest[i,1]= se[1,1];
msefe[i,1]=(feb[i,1]-betaM[i,1])^2;

clfe[i,1]=betaM[i,1]-(zstat*fest[i,1]);
cufe[i,1]=betaM[i,1]+(zstat*fest[i,1]);
if (clfe[i,1] <= feb[i,1]) AND (feb[i,1] <= cufe[i,1]);
    cintfe[i,1]=1;
endif;

clear se,e,s2,v,xfe,yfe,febi;



/************
*    CCEP   *
************/

ccepbi = invpd(xc'xc)*(xc'yc);
e  = yc - xc*ccepbi;
s2 = (e'e)/(nn*tt-(nn*2)-1-nn); /* df = obs - (k*N) - k - N intercepts */
v  = s2*invpd(xc'xc);
se = sqrt(diag(v));

cceb[i,1]=ccepbi[1,1];
ccest[i,1]= se[1,1];
msecce[i,1]=(cceb[i,1]-betaM[i,1])^2;

clcce[i,1]=betaM[i,1]-(zstat*ccest[i,1]);
cucce[i,1]=betaM[i,1]+(zstat*ccest[i,1]);
if (clcce[i,1] <= cceb[i,1]) AND (cceb[i,1] <= cucce[i,1]);
    cintcce[i,1]=1;
endif;
```

```
clear se,e,s2,v,xc,yc,ccepbi;


/************
*   FD OLS  *
************/

fdbi = invpd(dx'dx)*(dx'dy);
e  = dy - dx*fdbi;
s2 = (e'e)/(nn*tt-1-(tt-1)-0); /* df = obs - k - year dummies - no
intercepts */
v  = s2*invpd(dx'dx);
se = sqrt(diag(v));

fdb[i,1]=fdbi[1,1];
fdst[i,1]= se[1,1];
msefd[i,1]=(fdb[i,1]-betaM[i,1])^2;

clfd[i,1]=betaM[i,1]-(zstat*fdst[i,1]);
cufd[i,1]=betaM[i,1]+(zstat*fdst[i,1]);
if (clfd[i,1] <= fdb[i,1]) AND (fdb[i,1] <= cufd[i,1]);
    cintfd[i,1]=1;
endif;

/*
clear fdbi;
dx = dx~ydumfd;
fdbi = invpd(dx'dx)*(dx'dy);
*/
cdp=zeros(1,1) | fdbi[2:tt,1];
clear se,e,s2,v,dx,dy,fdbi;


/********************
*    Infeasible FE   *
********************/

inffebi = invpd(x'x)*(x'y);
e  = y - x*inffebi;
s2 = (e'e)/(nn*tt-1-(2*nn)-nn); /* df = obs - k - number of f's*N  - N
intercepts */
v  = s2*invpd(x'x);
se = sqrt(diag(v));

inffeb[i,1]=inffebi[1,1];
inffest[i,1]= se[1,1];
mseinffe[i,1]=(inffeb[i,1]-betaM[i,1])^2;

clinffe[i,1]=betaM[i,1]-(zstat*inffest[i,1]);
cuinffe[i,1]=betaM[i,1]+(zstat*inffest[i,1]);
if (clinffe[i,1] <= inffeb[i,1]) AND (inffeb[i,1] <= cuinffe[i,1]);
    cintinffe[i,1]=1;
endif;

clear se,e,s2,v,x,y,inffebi;



/***************************************************************************
*******************/
```

```
/* Country regressions */


/* Prep CCEMG and AMG */
/**********************/
xxxt=meanc(x_it.');
yyyt=meanc(y_it.'); /* vector of period averages for t=1,...,T*/

indx=vec(x_it)~ones(tt*nn,1);
xsec=ones(nn,1) .*. xxxt;
ysec=ones(nn,1) .*. yyyt;
indMy=vec(y_it);
indMya=vec(y_it)- ones(nn,1) .*. cdp;
indMx=indx~ysec~xsec;
indM0x=vec(x_it)~ysec~xsec;
trends=ones(nn,1) .*. seqa(0,1,tt);
tfp=ones(nn,1) .*. cdp;
tfp2=ones(nn,1) .*. f_1t~ones(nn,1) .*. f_2t;
indMxa=indx~trends;
clear xsec,ysec,undy,indx,indya;


/* Country estimates */
indccemgb1=zeros(nn,1);
indccemgse1=zeros(nn,1);
indamgb1=zeros(nn,1);
indamgse1=zeros(nn,1);
amg2b1=zeros(nn,1);
amg2se1=zeros(nn,1);
mgb1=zeros(nn,1);
mgse1=zeros(nn,1);
infmgb1=zeros(nn,1);
infmgse1=zeros(nn,1);

/* Begin loop */

for j(1,nn,1);

/*************
*    CCEMG   *
*************/
indx=indMx[(j-1)*tt+1:tt*j,.];
indy=indMy[(j-1)*tt+1:tt*j,.];
indccemgb1i  = invpd(indx'indx)*(indx'indy);
e  = indy - indx*indccemgb1i ;
s2 = (e'e)/(tt-4);
v  = s2*invpd(indx'indx);
se = sqrt(diag(v));
indccemgb1[j,.]=indccemgb1i[1,1];
indccemgse1[j,.] = se[1,1];
clear se,e,s2,v,indx,indy;

/**************
*    AMG(i)   *
**************/
indx=indMxa[(j-1)*tt+1:tt*j,.];
indy=indMya[(j-1)*tt+1:tt*j,.];
indamgb1i  = invpd(indx'indx)*(indx'indy);
e  = indy - indx*indamgb1i;
```

```
s2 = (e'e)/(tt-3);
v  = s2*invpd(indx'indx);
se = sqrt(diag(v));
indamgb1[j,.]=indamgb1i[1,1];
indamgse1[j,.]= se[1,1];
clear se,e,s2,v,indx,indy;

/*************/
/*  AMG(ii)  */
/*************/
infx=indMx[(j-1)*tt+1:tt*j,1:2]~tfp[(j-1)*tt+1:tt*j,1];
infy=indMy[(j-1)*tt+1:tt*j,.];
amg2b1i  = invpd(infx'infx)*(infx'infy);
e  = infy - infx*amg2b1i;
s2 = (e'e)/(tt-4);
v  = s2*invpd(infx'infx);
se = sqrt(diag(v));
amg2b1[j,.]=amg2b1i[1,1];
amg2se1[j,.]= se[1,1];
clear se,e,s2,v,infy,infx;

/************/
/* Naive MG */
/************/
indx=indMx[(j-1)*tt+1:tt*j,1:2]~trends[(j-1)*tt+1:tt*j,.];
indy=indMy[(j-1)*tt+1:tt*j,.];
mgb1i  = invpd(indx'indx)*(indx'indy);
mgb1[j,.]=mgb1i[1,1];
clear indy,indx;

/*****************/
/* Infeasible MG */
/*****************/
infx=indMx[(j-1)*tt+1:tt*j,1:2]~tfp2[(j-1)*tt+1:tt*j,.];
infy=indMy[(j-1)*tt+1:tt*j,.];
infmgb1i  = invpd(infx'infx)*(infx'infy);
e  = infy - infx*infmgb1i;
s2 = (e'e)/(tt-4);
v  = s2*invpd(infx'infx);
se = sqrt(diag(v));
infmgb1[j,.]=infmgb1i[1,1];
infmgse1[j,1]=se[1,1];
clear se,e,s2,v,infy,infx;


endfor;
/* End of loop of N country regressions */

/* Construct mean estimates from country estimates */
ccemgb[i,1]  = meanc(indccemgb1);
amgb[i,1] = meanc(indamgb1);
amg2b[i,1] = meanc(amg2b1);
mgb[i,1] = meanc(mgb1);
infmgb[i,1] = meanc(infmgb1);

/* Construct RMSE from mean estimates of country specific estimates */
mseccemg[i,1]=(ccemgb[i,1]-betaM[i,1])^2;
mseamg[i,1]=(amgb[i,1]-betaM[i,1])^2;
mseamg2[i,1]=(amg2b[i,1]-betaM[i,1])^2;
msemg[i,1]=(mgb[i,1]-betaM[i,1])^2;
mseinfmg[i,1]=(infmgb[i,1]-betaM[i,1])^2;
```

```
/* Construct standard errors for MG-type estimators */
ccemgdev=zeros(nn,1);
ccemgdev=indccemgb1-ones(nn,1) .* ccemgb[i,1];
ccemgdev=ccemgdev^2;
ccemgvar=sumc(ccemgdev)/(nn*(nn-1));
ccemgst[i,1]=sqrt(ccemgvar);

amgdev=zeros(nn,1);
amgdev=indamgb1-ones(nn,1) .* amgb[i,1];
amgdev=amgdev^2;
amgvar=sumc(amgdev)/(nn*(nn-1));
amgst[i,1]=sqrt(amgvar);

amg2dev=zeros(nn,1);
amg2dev=amg2b1-ones(nn,1) .* amg2b[i,1];
amg2dev=amg2dev^2;
amg2var=sumc(amg2dev)/(nn*(nn-1));
amg2st[i,1]=sqrt(amg2var);

mgdev=zeros(nn,1);
mgdev=mgb1-ones(nn,1) .* mgb[i,1];
mgdev=mgdev^2;
mgvar=sumc(mgdev)/(nn*(nn-1));
mgst[i,1]=sqrt(mgvar);

infmgdev=zeros(nn,1);
infmgdev=infmgb1-ones(nn,1) .* infmgb[i,1];
infmgdev=infmgdev^2;
infmgvar=sumc(infmgdev)/(nn*(nn-1));
infmgst[i,1]=sqrt(infmgvar);



/* Construct COverage Rate for the mean estimates of country specific
estimates */
clccemg[i,1]=betaM[i,1]-(zstat*ccemgst[i,1]);
cuccemg[i,1]=betaM[i,1]+(zstat*ccemgst[i,1]);
if (clccemg[i,1] <= ccemgb[i,1]) AND (ccemgb[i,1] <= cuccemg[i,1]);
    cintccemg[i,1]=1;
endif;


clamg[i,1]=betaM[i,1]-(zstat*amgst[i,1]);
cuamg[i,1]=betaM[i,1]+(zstat*amgst[i,1]);
if (clamg[i,1] <= amgb[i,1]) AND (amgb[i,1] <= cuamg[i,1]);
    cintamg[i,1]=1;
endif;


clamg2[i,1]=betaM[i,1]-(zstat*amg2st[i,1]);
cuamg2[i,1]=betaM[i,1]+(zstat*amg2st[i,1]);
if (clamg2[i,1] <= amg2b[i,1]) AND (amg2b[i,1] <= cuamg2[i,1]);
    cintamg2[i,1]=1;
endif;


clmg[i,1]=betaM[i,1]-(zstat*mgst[i,1]);
cumg[i,1]=betaM[i,1]+(zstat*mgst[i,1]);
if (clmg[i,1] <= mgb[i,1]) AND (mgb[i,1] <= cumg[i,1]);
```

```
    cintmg[i,1]=1;
endif;


clinfmg[i,1]=betaM[i,1]-(zstat*infmgst[i,1]);
cuinfmg[i,1]=betaM[i,1]+(zstat*infmgst[i,1]);
if (clinfmg[i,1] <= infmgb[i,1]) AND (infmgb[i,1] <= cuinfmg[i,1]);
    cintinfmg[i,1]=1;
endif;

/***************************************************************************
*******************/

/*********************
*    ITERATIONS end   *
**********************/


endfor;
/*********************************/
/* Efficiency Rate */
/*********************************/

effols=100*((sqrt(sumc(mseols)))/(sqrt(sumc(msefe))));
efffe=100*((sqrt(sumc(msefe)))/(sqrt(sumc(msefe))));
effcce=100*((sqrt(sumc(msecce)))/(sqrt(sumc(msefe))));
efffd=100*((sqrt(sumc(msefd)))/(sqrt(sumc(msefe))));
effinffe=100*((sqrt(sumc(mseinffe)))/(sqrt(sumc(msefe))));

effccemg=100*((sqrt(sumc(mseccemg)))/(sqrt(sumc(msemg))));
effamg=100*((sqrt(sumc(mseamg)))/(sqrt(sumc(msemg))));
effamg2=100*((sqrt(sumc(mseamg2)))/(sqrt(sumc(msemg))));
effmg=100*((sqrt(sumc(msemg)))/(sqrt(sumc(msemg))));
effinfmg=100*((sqrt(sumc(mseinfmg)))/(sqrt(sumc(msemg))));



/***************************************************************************
*******************/
"**************************************************************************";
betai=meanc(betaM);
if jj3==1;
    "Heterogeneous beta with mean: " betai;
elseif jj3==0;
    "Homogeneous beta: " betai;
endif;

/**********************
*    OUTPUT: Results   *
***********************/
format /rd 2,0;

t1 = date;
timing=round((ethsec(t0,t1)/100));
if timing<=60;
print "Total time since start of simulation: " timing " seconds";
elseif timing>60;
print "Total time since start of simulation: " timing/60 " minutes";
endif;
"***************************************************************************
*************************";
```

```
"Monte Carlo results: " iter "iterations  T=" tt " N=" nn ;
"***************************************************************************
**************************";
format /rd 2,4;
"               Mean      Median      emp.ste     mean ste    mean RMSE
Coverage    Efficiency Rate";
"---------------------------------------------------------------------------
---------------------------";
"POLS           " meanc(olsb) "    " median(olsb) "     " stdc(olsb) "
" meanc(olsst) "     " meanc(mseols) "     " meanc(cintols)*100 "     "
effols;
"FE             " meanc(feb) "    " median(feb) "     " stdc(feb) "     "
meanc(fest) "     " meanc(msefe) "     " meanc(cintfe)*100 "     " efffe;
"CCEP           " meanc(cceb) "    " median(cceb) "     " stdc(cceb) "
" meanc(ccest) "     " meanc(msecce) "     " meanc(cintcce)*100 "     "
effcce;
"FD             " meanc(fdb) "    " median(fdb) "     " stdc(fdb) "     "
meanc(fdst) "     " meanc(msefd) "     " meanc(cintfd)*100  "     " efffd;
"Infeasible FE  " meanc(inffeb) "    " median(inffeb) "     " stdc(inffeb)
"     " meanc(inffest) "     " meanc(mseinffe) "     " meanc(cintinffe)*100
"     " effinffe;
"---------------------------------------------------------------------------
-----------------------------";
"CCEMG          " meanc(ccemgb) "    " median(ccemgb) "     " stdc(ccemgb)
"     " meanc(ccemgst) "     " meanc(mseccemg) "     " meanc(cintccemg)*100
"     " effccemg;
"AMG(i)         " meanc(amgb) "    " median(amgb) "     "  stdc(amgb) "
" meanc(amgst) "     " meanc(mseamg) "     " meanc(cintamg)*100 "     "
effamg;
"AMG(ii)        " meanc(amg2b) "    " median(amg2b) "     "  stdc(amg2b) "
" meanc(amg2st) "     " meanc(mseamg2) "     " meanc(cintamg2)*100 "     "
effamg2;
"MG             " meanc(mgb) "    " median(mgb) "     " stdc(mgb) "     "
meanc(mgst) "     " meanc(msemg) "     " meanc(cintmg)*100 "     " effmg;
"MG (true f's)  " meanc(infmgb) "    " median(infmgb) "     " stdc(infmgb)
"     " meanc(infmgst) "     " meanc(mseinfmg) "     " meanc(cintinfmg)*100
"     " effinfmg;
"---------------------------------------------------------------------------
------------------------------";
"";
"";

endfor;
endfor;
endfor;
endfor;
endfor;
endfor;

output off;

end;
```

7.5 Income Elasticity of Healthcare Expenditure

```
clear
//Change the .ado file directory to my P drive
sysdir set OLDPLACE "P:\Desktop\ado"

sysdir set PLUS "P:\Desktop\ado\plus"
```

```
use "\\file\UsersA$\aaa121\Home\Desktop\Fragile paper
Rework\Data\Estimation\H-I 54 African Countries Full.dta"

cd "\\file\UsersA$\aaa121\Home\Desktop\Fragile paper
Rework\Data\Estimation"

xtset cid year

mdesc *

//Somalia and South sudan have missing observations for all the variables
excluding LEX, INM

drop if country == "Somalia"

drop if country == "South Sudan"

mdesc *

//use "\\file\UsersA$\aaa121\Home\Desktop\Fragile paper
Rework\Data\Estimation\H-I 52 African
Countries_excluding_Somalia_and_South_Sudan.dta"


//**********Exclude countries with over 10 observations for GFC ********//

/**/
drop if country == "Cabo Verde"
drop if country == "Ethiopia"
drop if country == "Lesotho"
drop if country == "Sao Tome and Principe"
drop if country == "Zambia"

mdesc *
**/

summarize the ghe ope gdp lex inm p15 p65 oda gfc

gen lthe = log(the)
gen lghe = log(ghe)
gen lope = log(ope)
gen lgdp = log(gdp)
gen llex = log(lex)
gen linm = log(inm)
gen lp15 = log(p15)
gen lp65 = log(p65)
gen loda = log(oda)
gen lgfc = log(gfc)


gen dlthe = d.lthe
gen dlghe = d.lghe
gen dlope = d.lope
gen dlgdp = d.lgdp
gen dllex = d.llex
gen dlinm = d.linm
gen dlp15 = d.lp15
gen dlp65 = d.lp65
gen dloda = d.loda
gen dlgfc = d.lgfc
```

```
****************************
/**Baseline Analysis**/
****************************
//ereturn list
//di e(b)
//matrix list e(b)
eststo m1: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba11)
di e(trend_sig)
test lgdp = 1

eststo m2: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba21)
di e(trend_sig)
test lgdp = 1

eststo m3: xtmg lope lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba31)
di e(trend_sig)
test lgdp = 1

esttab m1 m2 m3 using baselineresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba11 ba21 ba31
multipurt ba11 ba21 ba31, lags(1)

****************************
/** Test of Slope Heterogeneity**/
****************************
xtrc lthe lgdp llex linm lp65 lp15 loda lgfc, vce(conventional)
xtrc lghe lgdp llex linm lp65 lp15 loda lgfc, vce(conventional)
xtrc lope lgdp llex linm lp65 lp15 loda lgfc, vce(conventional)


****************************
/**Alternative Specification Without Trend**/
****************************
eststo m4: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc, cce robust
res(ba12)
test lgdp = 1

eststo m5: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc, cce robust
res(ba22)
test lgdp = 1

eststo m6: xtmg lope lgdp llex linm lp65 lp15 loda lgfc, cce robust
res(ba32)
test lgdp = 1

esttab m4 m5 m6 using alternativeresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba12 ba22 ba32
multipurt ba12 ba22 ba32, lags(1)

****************************
/**Pooled Type Estimators**/
****************************
/**** POLS Method****/
reg lthe lgdp llex linm lp65 lp15 loda lgfc cid#c.year, vce(robust)
eststo m7
```

```
predict ba13, residual
estat ovtest
di e(rmse)
estat ic
test lgdp = 1

reg lghe lgdp llex linm lp65 lp15 loda lgfc cid#c.year, vce(robust)
eststo m8
predict ba23, residual
estat ovtest
di e(rmse)
estat ic
test lgdp = 1

reg lope lgdp llex linm lp65 lp15 loda lgfc cid#c.year, vce(robust)
eststo m9
predict ba33, residual
estat ovtest
di e(rmse)
estat ic
test lgdp = 1

esttab m7 m8 m9 using pooledestimatorresults.csv, star(* 0.10 ** 0.05 ***
0.01)

xtcd ba13 ba23 ba33
multipurt ba13 ba23 ba33, lags(1)


/****Fixed Effect Method****/
reg lthe lgdp llex linm lp65 lp15 loda lgfc cid##c.year, vce(cluster cid)
eststo m10
predict ba14, residual
test lgdp = 1
xtserial lthe lgdp llex linm lp65 lp15 loda lgfc
di e(rmse)
estat ic


reg lghe lgdp llex linm lp65 lp15 loda lgfc cid##c.year, vce(cluster cid)
eststo m11
predict ba24, residual
test lgdp = 1
xtserial lghe lgdp llex linm lp65 lp15 loda lgfc
di e(rmse)
estat ic


reg lope lgdp llex linm lp65 lp15 loda lgfc cid##c.year, vce(cluster cid)
eststo m12
predict ba34, residual
test lgdp = 1
xtserial lope lgdp llex linm lp65 lp15 loda lgfc
di e(rmse)
estat ic

esttab m10 m11 m12 using FEresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba14 ba24 ba34
multipurt ba14 ba24 ba34, lags(1)
```

```
*****************************
/**AMG Estimator**/
*****************************
eststo m13: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc, aug trend robust
res(ba15)
di e(trend_sig)
test lgdp = 1

eststo m14: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc, aug trend robust
res(ba25)
di e(trend_sig)
test lgdp = 1

eststo m15: xtmg lope lgdp llex linm lp65 lp15 loda lgfc, aug trend robust
res(ba35)
di e(trend_sig)
test lgdp = 1

esttab m13 m14 m15 using AMGresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba15 ba25 ba35
multipurt ba15 ba25 ba35, lags(1)


*****************************
/**Income Group: Data Decomposition**/
*****************************


/****Low Middle Income****/

eststo m16: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LMI", cce trend robust res(ba16)
di e(trend_sig)
test lgdp = 1


eststo m17: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LMI", cce trend robust res(ba26)
di e(trend_sig)
test lgdp = 1


eststo m18: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LMI", cce trend robust res(ba36)
di e(trend_sig)
test lgdp = 1

esttab m16 m17 m18 using LMIresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba16 ba26  ba36
multipurt ba16 ba26 ba36, lags(1)


/****Upper Middle Income****/

eststo m19: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"UMI", cce trend robust res(ba17)
di e(trend_sig)
test lgdp = 1
```

```
eststo m20: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"UMI", cce trend robust res(ba27)
di e(trend_sig)
test lgdp = 1


eststo m21: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"UMI", cce trend robust res(ba37)
di e(trend_sig)
test lgdp = 1

esttab m19 m20 m21 using UMIresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba17 ba27  ba37
multipurt ba17 ba27 ba37, lags(1)


/****Low Income****/

eststo m22: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LIN", cce trend robust res(ba18)
di e(trend_sig)
test lgdp = 1


eststo m23: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LIN", cce trend robust res(ba28)
di e(trend_sig)
test lgdp = 1


eststo m24: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if income_group ==
"LIN", cce trend robust res(ba38)
di e(trend_sig)
test lgdp = 1

esttab m22 m23 m24 using LINresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba18 ba28  ba38
multipurt ba18 ba28 ba38, lags(1)


/****High Income****/

reg lthe lgdp llex linm lp65 lp15 loda lgfc cid#c.year if income_group ==
"HIN", vce(robust)
eststo m25
predict ba19, residual
test lgdp = 1
estat ovtest
di e(rmse)
estat ic



reg lghe lgdp llex linm lp65 lp15 loda lgfc cid#c.year if income_group ==
"HIN", vce(robust)
eststo m26
predict ba29, residual
test lgdp = 1
```

```
estat ovtest
di e(rmse)
estat ic



reg lope lgdp llex linm lp65 lp15 loda lgfc cid#c.year if income_group ==
"HIN", vce(robust)
eststo m27
predict ba39, residual
test lgdp = 1
estat ovtest
di e(rmse)
estat ic


esttab m25 m26 m27 using HINresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba19 ba29 ba39
multipurt ba19 ba29 ba39, lags(1)


*****************************
/**Geographical Region: Data Decomposition**/
*****************************

/****Sub-Saharan Africa****/

eststo m28: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if region ==
"SSA", cce trend robust res(ba110)
di e(trend_sig)
test lgdp = 1


eststo m29: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if region ==
"SSA", cce trend robust res(ba210)
di e(trend_sig)
test lgdp = 1


eststo m30: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if region ==
"SSA", cce trend robust res(ba310)
di e(trend_sig)
test lgdp = 1

esttab m28 m29 m30 using SSAresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba110 ba210 ba310
multipurt ba110 ba210 ba310, lags(1)


/****North Africa****/

eststo m31: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if region == "NA",
cce trend robust res(ba111)
di e(trend_sig)
test lgdp = 1


eststo m32: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if region == "NA",
cce trend robust res(ba211)
```

```
di e(trend_sig)
test lgdp = 1


eststo m33: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if region == "NA",
cce trend robust res(ba311)
di e(trend_sig)
test lgdp = 1

esttab m31 m32 m33 using NAresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba111 ba211 ba311
multipurt ba111 ba211 ba311, lags(1)

*****************************
/**Fragility Status: Data Decomposition**/
*****************************

/****Fragile Countries***/

eststo m34: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if fragility ==
"FRA", cce trend robust res(ba112)
di e(trend_sig)
test lgdp = 1


eststo m35: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if fragility ==
"FRA", cce trend robust res(ba212)
di e(trend_sig)
test lgdp = 1


eststo m36: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if fragility ==
"FRA", cce trend robust res(ba312)
di e(trend_sig)
test lgdp = 1

esttab m34 m35 m36 using FRAresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba112 ba212 ba312
multipurt ba112 ba212 ba312, lags(1)


/****Non-Fragile Countries****/


eststo m37: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if fragility  ==
"NFR", cce trend robust res(ba113)
di e(trend_sig)
test lgdp = 1


eststo m38: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if fragility ==
"NFR", cce trend robust res(ba213)
di e(trend_sig)
test lgdp = 1


eststo m39: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if fragility ==
"NFR", cce trend robust res(ba313)
di e(trend_sig)
```

```
test lgdp = 1

esttab m37 m38 m39 using NFRresults.csv, star(* 0.10 ** 0.05 *** 0.01)

xtcd ba113 ba213 ba313
multipurt ba113 ba213 ba313, lags(1)



*****************************
/**Sensitivity to Exchange Rate Fluctuations**/
*****************************
gen str ppp = "STABLE"

label variable ppp "Stable & UnStable Exchange Rate Country"

replace ppp = "UNSTABLE" if country == "Burundi"
replace ppp = "UNSTABLE" if country == "Congo, Dem. Rep."
replace ppp = "UNSTABLE" if country == "Guinea"
replace ppp = "UNSTABLE" if country == "Madagascar"
replace ppp = "UNSTABLE" if country == "Sierra Leone"
replace ppp = "UNSTABLE" if country == "Tanzania"
replace ppp = "UNSTABLE" if country == "Uganda"

/****UNSTABLE Countries****/
eststo m40: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc if ppp  ==
"UNSTABLE", cce trend robust res(ba114)
di e(trend_sig)
test lgdp = 1


eststo m41: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc if ppp  ==
"UNSTABLE", cce trend robust res(ba214)
di e(trend_sig)
test lgdp = 1


eststo m42: xtmg lope lgdp llex linm lp65 lp15 loda lgfc if ppp  ==
"UNSTABLE", cce trend robust res(ba314)
di e(trend_sig)
test lgdp = 1

esttab m40 m41 m42 using unstableppresults.csv, star(* 0.10 ** 0.05 ***
0.01)

xtcd ba114 ba214 ba314
multipurt ba114 ba214 ba314, lags(1)

**Drop countries with trending PPP series
drop if country == "Burundi"
drop if country == "Congo, Dem. Rep."
drop if country == "Guinea"
drop if country == "Madagascar"
drop if country == "Sierra Leone"
drop if country == "Tanzania"
drop if country == "Uganda"

eststo m43: xtmg lthe lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba115)
di e(trend_sig)
test lgdp = 1
```

```
eststo m44: xtmg lghe lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba215)
di e(trend_sig)
test lgdp = 1

eststo m45: xtmg lope lgdp llex linm lp65 lp15 loda lgfc, cce trend robust
res(ba315)
di e(trend_sig)
test lgdp = 1

esttab m43 m44 m45 using stablepppresults.csv, star(* 0.10 ** 0.05 ***
0.01)

xtcd ba115 ba215 ba315
multipurt ba115 ba215 ba315, lags(1)
```

GRAPHS

```
clear
//Change the .ado file directory to my P drive
sysdir set OLDPLACE "P:\Desktop\ado"

sysdir set PLUS "P:\Desktop\ado\plus"

use "\\file\UsersA$\aaa121\Home\Desktop\Fragile paper
Rework\Data\Estimation\ppp_data.dta"


xtset cid year

gen lrhex = log(rhex)


//Somalia and South sudan have missing observations for all the variables
excluding LEX, INM

drop if country == "Somalia"

drop if country == "South Sudan"

//**********Exclude countries with over 10 observations for GFC ********//

/**/
drop if country == "Cabo Verde"
drop if country == "Ethiopia"
drop if country == "Lesotho"
drop if country == "Sao Tome and Principe"
drop if country == "Zambia"

mdesc *
**/

summarize ppp_con reer rhex

correlate lrhex ppp_con

xtline ppp_con if cid < 25, i(country) t(year)
xtline ppp_con if cid > 24, i(country) t(year)

xtline lrhex if cid < 25, i(country) t(year)
xtline lrhex if cid > 24, i(country) t(year)
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Appendix: Chapter 2

Figure A2.1: HCE Per Capita Growth vs. Wages Per Employee Growth in OECD (1960-2005)

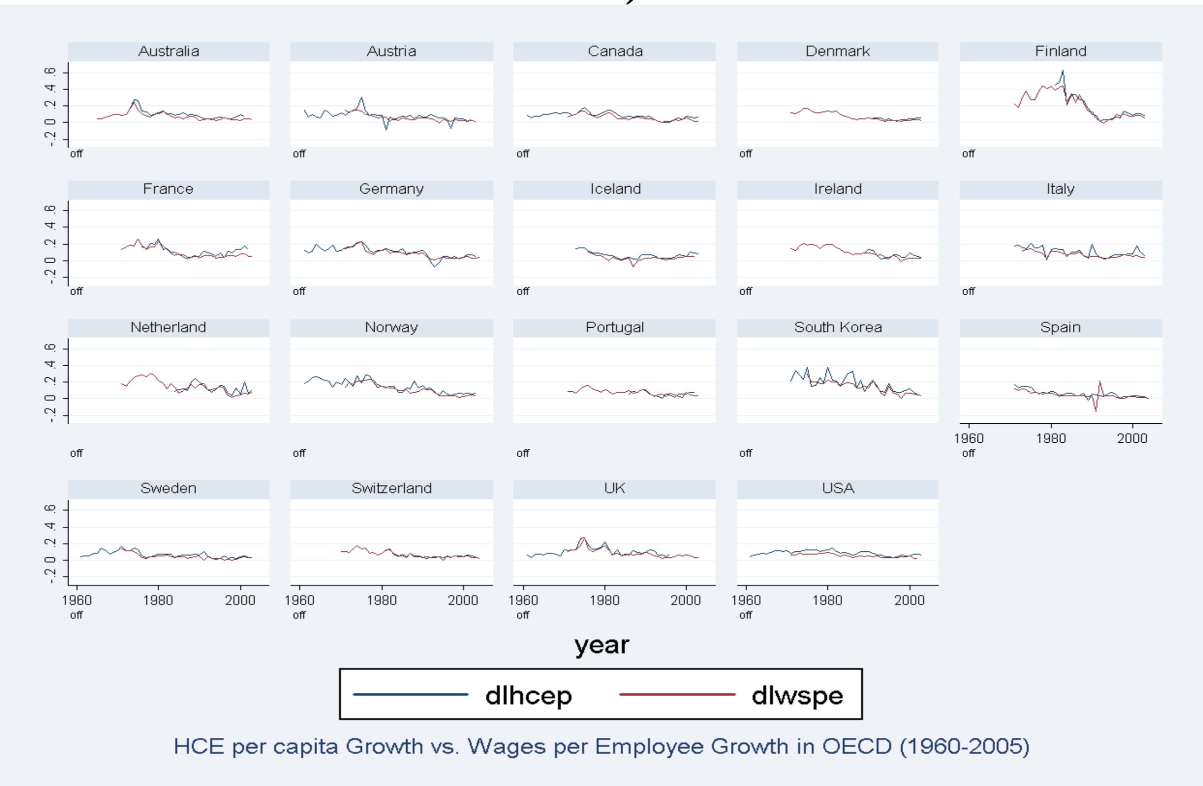


Figure A2.2: HCE Per Capita Growth vs. Baumol's Variable in OECD (1960-2005)

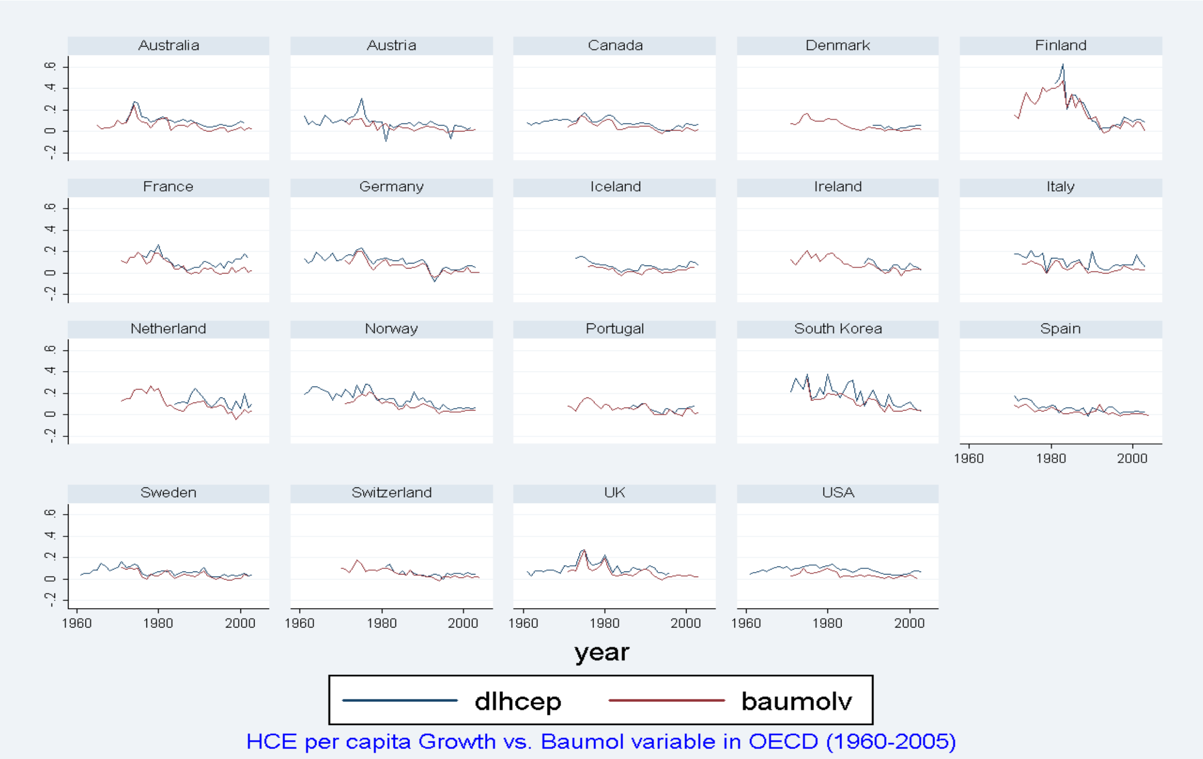


Figure A2.3: Size of Baumol's Effect in OECD using Random Coefficient Model

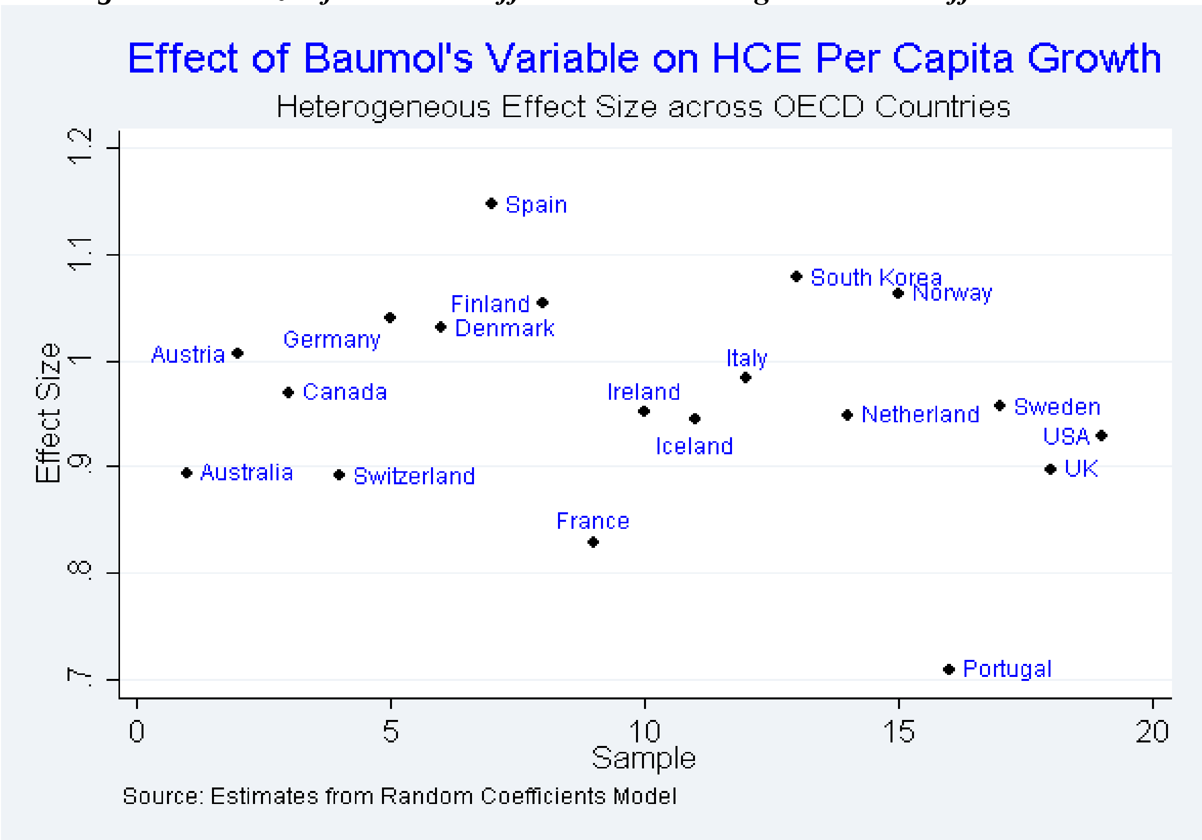


Figure A2.4: Size of Baumol's Effect in OECD using Mean Group Estimator

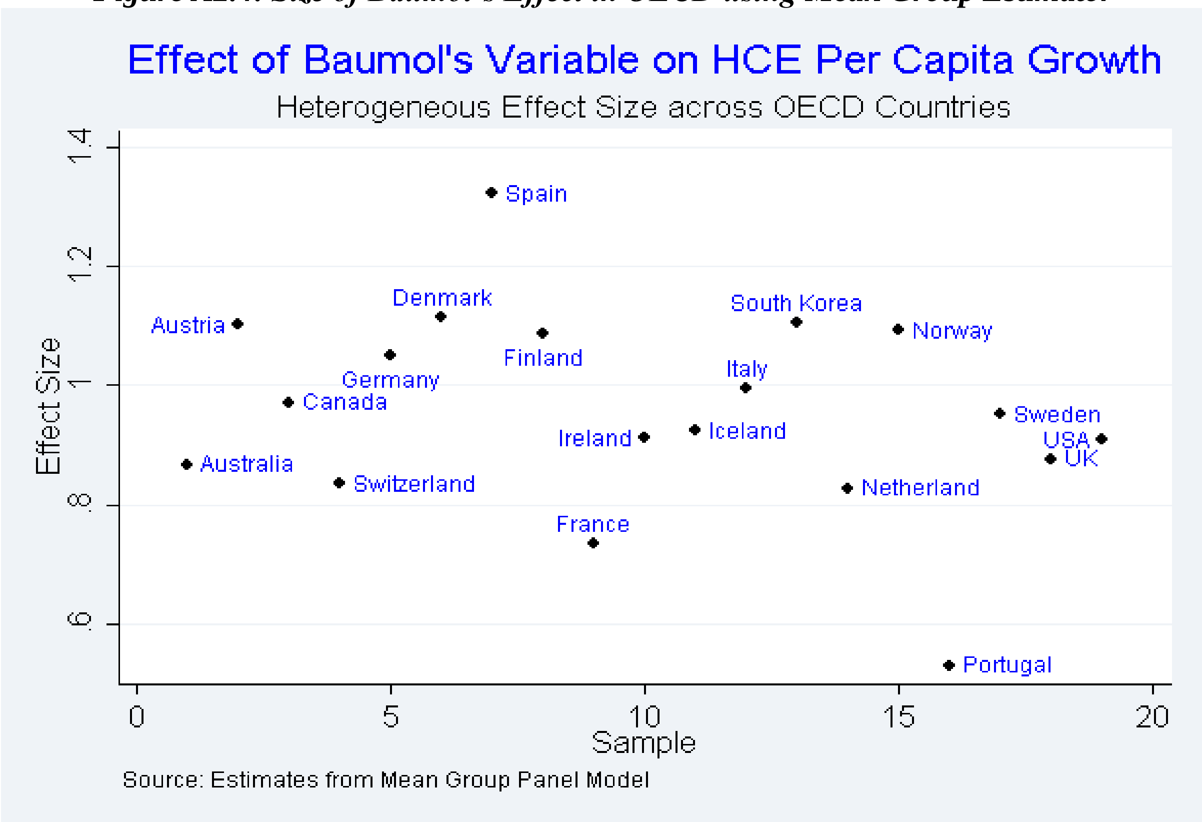


Figure A2.5: Size of Baumol's Effect in OECD using CCEMG Estimator

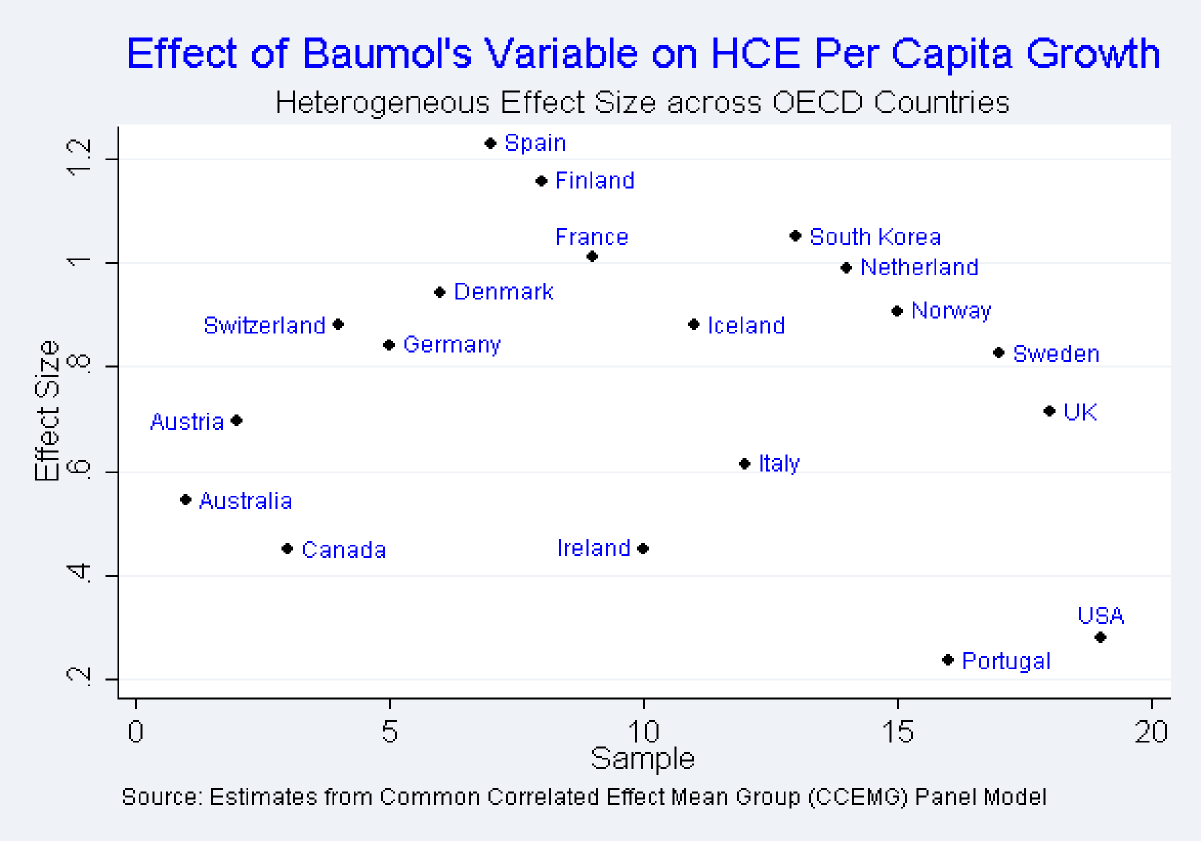
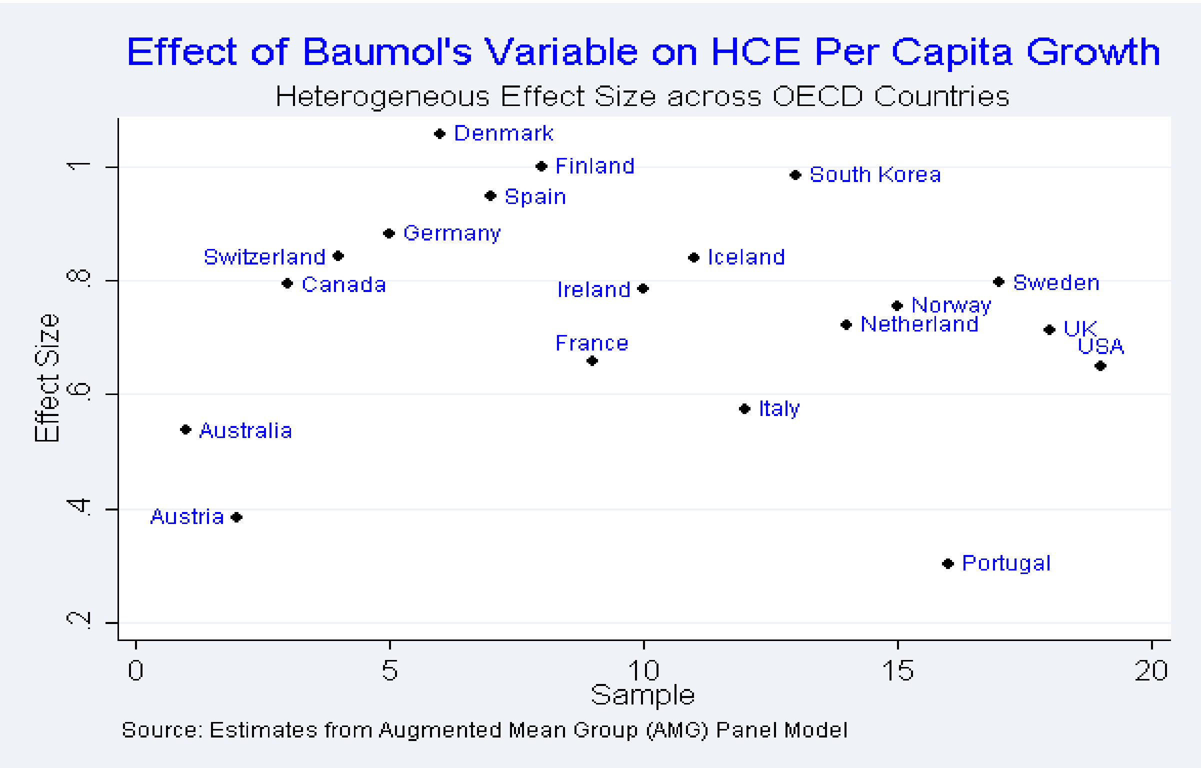


Figure A2.6: Size of Baumol's Effect in OECD using AMG Estimator



DESCRIPTION OF CROSS-SECTIONAL DEPENDENCE TEST

The cross-sectional dependence test is based on the following null and alternative hypotheses:

$$H_0 : \rho_{ij} = \rho_{ji} = cor(e_{it}, e_{jt}) = 0 \qquad \text{for } i \neq j$$

$$H_1 : \rho_{ij} = \rho_{ji} = cor(e_{it}, e_{jt}) \neq 0 \qquad \text{for some } i \neq j$$

where ρ_{ij} is the product-moment correlation coefficient of the disturbances and is given by

$$\rho_{ij} = \rho_{ji} \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}} \tag{A2.1}$$

The number of possible pairing (e_{it}, e_{jt}) can be derived from $N(N-1)$ and it rises with number of cross-section units (N).

I. Pesaran's Cross-Section Dependence (CD) Test

The null hypothesis of cross-sectional independence can be tested using the Pesaran (2004) CD test for unbalanced panels given by

$$PCD = \sqrt{\frac{2}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}}\, \hat{\rho}_{ij} \right) \tag{A2.2}$$

where $T_{ij} = \#(T_i \cap T_j)$ i.e., the number of common time-series observations between cross-section units i and j

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} \frac{\sum_{t \in T_i \cap T_j} \left(\hat{e}_{it} - \bar{\hat{e}}_i\right)\left(\hat{e}_{jt} - \bar{\hat{e}}_j\right)}{\left(\sum_{t \in T_i \cap T_j} \left(\hat{e}_{it} - \bar{\hat{e}}_i\right)^2\right)^{1/2} \left(\sum_{t \in T_i \cap T_j} \left(\hat{e}_{jt} - \bar{\hat{e}}_j\right)^2\right)^{1/2}} \tag{A2.3}$$

and

$$\bar{\hat{e}}_i = \frac{\sum_{t \in T_i \cap T_j} \hat{e}_{it}}{\#\left(T_i \cap T_j\right)} \tag{A2.4}$$

II. Friedman's Test

A nonparametric test advanced by Friedman (1937) was based on Spearman's rank correlation coefficient given by

$$r_{ij} = r_{ji} \frac{\sum_{t=1}^{T} \{r_{i,t} - (T+1/2)\}\{r_{j,t} - (T+1/2)\}}{\sum_{t=1}^{T} \{r_{i,t} - (T+1/2)\}^2} \tag{A2.5}$$

where $\{r_{i,1},...,r_{i,T}\}$ is the ranks of $\{u_{i,1},...,u_{i,T}\}$, and $(T+1/2)$ is the average rank. From the expression (A2.5), Friedman's statistic is based on the average correlation given as:

$$R_{ave} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{r}_{ij} \tag{A2.6}$$

If the value of R_{ave} is large, it suggests existence of nonzero cross-sectional correlation and Friedman showed that $FR = (T-1)\{(N-1)R_{ave} + 1\}$ is asymptotically χ^2 distributed with $T-1$ degree of freedom, for fixed T as N gets large.

De Hoyos and Sarafidis (2006) noted that PCD and R_{ave} involves the sum of the pairwise correlation coefficients of the residual matrix, and the tests are likely to miss cases of cross-sectional dependence where the sign of the correlations is alternating[53]. Although, if the

[53] The alternating correlation coefficients is a case where the coefficient values cancels out during averaging as a presence of large negative and positive correlation values in the residuals.

panel-data model is of single factor error structure (i.e. $e_{i,t} = \phi_i f_t + \varepsilon_{it}$) and the factor loadings mean are non-zero (i.e. $E(\phi_i) \neq 0$), then the PCD and R_{ave} tests would be reliable and not undergo such alternating signs problem.

III. Frees' Test

To avert the problem of factor loading being mean zero resulting from correlation coefficients of the error term alternate in signs (making PCD and R_{ave} inappropriate and less reliable), Frees (1995); (2004) proposed a statistic based on the sum of the squared rank correlation coefficient and equals:

$$R_{avr}^2 = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{r}_{ij}^2 \qquad \text{(A2.7)}$$

Frees indicated that the statistic follows a joint distribution of two independently drawn χ^2 variables as follows:

$$FRE = N\left\{R_{ave} - (T-1)^{-1}\right\} \xrightarrow{d} Q = a(T)\left\{x_{1,T-1}^2 - (T-1)\right\} + b(T)\left\{x_{2,T(T-3)/2}^2 - T(T-3)/2\right\} \qquad \text{(A2.8)}$$

where $x_{1,T-1}^2$ and $x_{2,T(T-3)/2}^2$ are the independent χ^2 random variables with respective $T-1$ and $T(T-3)/2$ degree of freedom. Also, $a(T) = 4(T+2)/\left\{5(T-1)^2(T+1)\right\}$ and $b(T) = 2(5T+6)/\left\{5T(T-1)(T+1)\right\}$.

However, the null hypothesis is rejected when $R_{avr}^2 > \left\{(T-1)^{-1} + Q_q / N\right\}$ and Q_q is the appropriate quantile of the Q distribution and a weighted sum of two χ^2 -randomly distributed variables and depends on the size of T . For T tending from 20 to 30, the normal approximation to Q distribution performs well.

Table A2.1: Brief Description and Set-up of Panel Data Estimators

Properties	POLS	Random Effect Model	Random Coefficients Model	Mean Group	Common Correlated Effect MG	Augmented Mean Group
Model	Static	Static	Static	Static/Dynamic	Static/Dynamic	Static/Dynamic
Data Set	Asymptotically unbiased as $(N,T)\to\infty$	Asymptotically unbiased as $(N,T)\to\infty$	Large (N,T)	Large (N,T)	Large (N,T)	Large (N,T)
Specification	$y_{i,t}=\alpha+\beta' x_{i,t}+u_{i,t}$	$y_{i,t}=\alpha+\beta' x_{i,t}+\varepsilon_{i,t}$ $\varepsilon_{i,t}=\mu_i+e_{i,t}$ $\varepsilon_{i,t}=\gamma_t+e_{i,t}$	$y_{i,t}=\alpha_i+\beta_i' x_{i,t}+u_{i,t}$	$y_{i,t}=\alpha_i+\beta_i' x_{i,t}+u_{i,t}$ $\varepsilon_{i,t}=\mu_i+\gamma_t+e_{i,t}$	$y_{i,t}=\beta_i' x_{i,t}+u_{i,t}$ $\varepsilon_{i,t}=\alpha_{1i}+\lambda_i f_t+e_{i,t}$ $x_{i,t}=\alpha_{2i}+\lambda_i f_t$ $+\eta_i g_t+\omega_{i,t}$	$y_{i,t}=\beta_i' x_{i,t}+u_{i,t}$ $\varepsilon_{i,t}=\alpha_{1i}+\lambda_i f_t+e_{i,t}$ $x_{i,t}=\alpha_{2i}+\lambda_i f_t$ $+\eta_i g_t+\omega_{i,t}$
Panel Series/ Observable variables Properties (assumed)	Stationary	Stationary	Stationary	Stationary	Non-Stationary	Non-Stationary
Unobservable/ Residual series Properties (assumed)	Stationary	Stationary	Stationary	Stationary	Non-stationary	Non-stationary
Cross-section correlation of residuals (assumed)	Cross-sectional Independence	Cross-sectional Independence	Cross-sectional Independence	Cross-sectional Independence	Cross-sectional Dependence	Cross-sectional Dependence
Intercept	$\alpha_i\equiv\alpha$	$\alpha_i=\alpha+\mu_i$	Heterogeneous	Heterogeneous	Heterogeneous	Heterogeneous
Slope (β)	Constant for all i	Constant for all i	Heterogeneous & Random ($\beta_i=\beta+\mu_i$)	Heterogeneous (Long-run, non-random & simple average of β_i)	Heterogeneous	Heterogeneous

Properties	**POLS**	**Random Effect Model**	**Random Coefficients Model**	**Mean Group**	**Common Correlated Effect MG**	**Augmented Mean Group**
Factor(s) Loading (assumed)	Homogeneous and Stationary	Homogeneous and Stationary	Homogeneous and Stationary	Homogeneous and Stationary	-heterogeneous - f_t and g_t can be linear or non-linear -nonstationary i.e. $f_t = \phi' f_{t-1} + \xi_t$ $g_t = \kappa' g_{t-1} + \xi_t$ - f_t is treated as nuisance -Robust to presence of finite 'strong' factors -Robust to presence of unlimited 'weak' factors/shocks	-heterogeneous - f_t and g_t can be linear or non-linear and nonstationary - f_t is treated as unobservable factor productivity
Assumed $Corr(\mu_i, X)$	$Corr(\mu_{i`}, X) = 0$	$Corr(\mu_{i`}, X) = 0$	$Corr(\mu_{i`}, X) = 0$	$Corr(\mu_{i`}, X) = 0$	$Corr(\mu_{i`}, X) \neq 0$	$Corr(\mu_{i`}, X) \neq 0$

Properties	POLS	Random Effect Model	Random Coefficients Model	Mean Group	Common Correlated Effect MG	Augmented Mean Group
Treatment Endogeneity (created by common factor structure (f_t))					-Augment with $\bar{y}_t$ & $\bar{x}_t$ to accounts for the unobservable common shock/factor (f_t)	-Augment with $\bar{\hat{\rho}}_t$ (common dynamic process) i.e. the estimated cross-section average of the unobservable factor productivity over time. Where $\hat{\rho}_t$ is from $\Delta y_{i,t} = \beta' \Delta x_{i,t} + \rho \Delta TD_{i,t}$ and TD is year dummies.

Source: Banerjee, Eberhardt, & Reade, 2010; Beck & Katz, 2007; Bond & Eberhardt, 2009; Chudik & Pesaran, 2013; Eberhardt & Teal, 2010, 2011, 2014; Pesaran, 2006; Pesaran & Smith, 1995; Poi, 2003; Reed & Ye, 2011; Swamy, 1970

Appendix: Chapter 3

Table A3.1: Review of Literature on Baumol's Cost Disease in the Health Industry

S/N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
1	**Baumol (1993)**	Health care, education and the cost disease: A looming crisis for public choice	Provides explanation and a solution for the rising cost of health care and education	Service (Education and Health) and Goods (Manufacturing and Agriculture) sectors in United States (1990 and 2040)	Trend review of Productivity and total Spending growth	Productivity (service share of GNP per labour) hours and real expenditure for number of labour hours employed			Bar charts	Prices in the service sector will continue to rise at a rate beyond control because of costs of service in terms of labour inputs and declining labour productivity. The cost disease implies that governments are faced with a daunting task of acquiring adequate revenues to prevent municipal services from collapsing. Then, these services constitutes a larger share of public budgets

S/ N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
2	**Nixon & Ulmann (2006)**	The relationship between Health care expenditure and Health outcomes: Evidence and caveats for a causal link	Examines the effect of health care expenditure on health outcomes	15 EU countries (1980-1995)	Link the basic axioms of BCD hypothesis from demand side				No analytical framework to examine BCD	He explains the application of BCD in the health care industry based on the increasing long demand for the sector activities. He explains that there is unlimited demand for better health care services as long as people experience variation in their health status and spending in the sector as a share of national income increases overtime because of its low productivity activities.
3	**Martins & Maisonneuve (2006)**	The drivers of public expenditure on health and long-term health care: An integrated projection approach	Examines the relative relevance of demographic and non-demographic factors in projecting public & long-term health expenditures	30 OECD countries (1981-2002; 2005-2050)	Labour costs or wage growth approach	Baumol effect is assumed to be unit costs of labour that rises with aggregate labour productivity in the economy	Growth of long-term care expenditure per output [LTC/]	Baumol effect; age factor; share of informal care	Fixed effect panel model	The long-term care expenditure per dependent shifts upwards due to the "cost-disease" effect by an average of 2.2% and expected to be 3.3% by 2050.

S/ N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
4	**Hartwig (2008b)**	What drives health care expenditure? – Baumol's model of 'unbalanced growth' revisited	Revisit the Baumol's theory in explaining the continuous rise in health care expenditure	19 OECD countries (1960-2005)	Wage-productivity growth gap approach	Baumol variable is the growth difference between nominal wages per employee and labour productivity (real GDP/L) in the overall economy	Log difference of health care expenditure per capita	Log difference of: Wages and salaries per employee in the overall economy; real GDP; overall employment; Baumol variable; GDP deflator; GDP per capita; real GDP per capita	Pooled OLS; Cross-section Random Effect; Time Period Random Effect	Health care expenditure per capita growth effect of Baumol variable was positive and ranges between 1.029 and 1.033. The study validated the Baumol hypothesis and concluded that Baumol effect on HCE growth is approximately one.

S/N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
5	**Hartwig (2008a)**	Has health capital formation cured Baumol's Disease? Panel Granger causality evidence for OECD countries	Examine the effect of expenditure shifts into the health sector (as a service sector whose productivity is low) on overall GDP growth	21 OECD countries (1970-2005)	Output-Expenditure Growth nexus approach	Health care expenditure per capita growth as a proxy for all-round "cost disease". Hartwig justify the measure on the basis that the periods of strong increases in HCE are seen as episodes in which employment and expenditures shift to a sector with low productivity growth.	GDP per capita growth	HCE per capita growth; two lags of GDP per capita growth and HCE per capita growth	OLS; Arellano-Bond one-step system GMM; and Arellano-Bond two-step system GMM	All the lags of Baumol effect (i.e. lagged HCE growth) had negative and significant impact on GDP per capita growth rate. The Baumol effect coefficients ranges from -0.074 to -0.179. This indicates that expenditure shifts into the health sector declines overall GDP growth. Thus supports the predictions of Baumol's model of unbalanced growth

S/ N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
6	**Hartwig (2011)**	Can Baumol's model of unbalanced growth contribute to explaining the secular rise in health care expenditure? An alternative test	Test the effect of relative price of medical care on variations in health expenditure as an alternative approach to validate Baumol's theory	9 OECD countries (1971-2003)	Relative price approach	Baumol's effect is measured as price of health care relative to GDP deflator	Log difference of health care expenditure per capita	Log difference of: price of health care relative to GDP deflator; GDP deflator; real GDP per capita; population age 65 and above	Pooled OLS; Cross-section Random Effect; Time Period Random Effect	Growth rate of relative medical care prices exert positive and significant effect on rising HCE. Thus supports the evidence of Baumol's hypothesis. The Baumol effect coefficient ranges between 0.381 and 0.512.
7	**Colombier (2012)**	Drivers of health care expenditure: Does Baumol's cost disease loom large	Demonstrate that the unavoidable secular rise in HCE suffers from Baumol 's cost disease to a MINOR extent compared to Hartwig findings	20 OECD countries (1965-2007)	Wage-productivity growth gap approach (but adjusted by a ratio of total employment)	Adjusted Baumol variable is the growth difference between real wage rate and labour productivity (real GDP/L) as ratio of total employment	Growth of HCE per capita	Adjusted Baumol variable; GDP per capita; population age 65 and above; infant mortality rate; life expectancy; death rate; R&D for pharmaceuticals	Static Two-way fixed effect; Static one-way (time effect) random effect	The study supports that health care sector is trapped by Baumol's cost disease between a positive and significant range of 0.109 and 0.212 growth effect. But the effect is less than proportional as indicated by Hartwig (2008). They also provide supports that inflation in health care sector is overestimated due to difficulties in a reliable medical price index

S/N	Author(s)/ (Year)	Title	Objective	Scope	BCD Approach	Measurement of Baumol's Variable	Dependent	Independent	Method	Findings/ Conclusion
8	**Bates & Santerre (2013)**	Does the U.S. health care sector suffer from Baumol's cost disease? Evidence from the 50 states	Examines if health care expenditures in the United States are affected by Baumol's cost disease	50 U.S. states (1980-2009)	Wage-productivity growth gap approach (with adjusted health care labour share)	Baumol variable is the growth difference between nominal wages and salaries per person employed and labour productivity (real Gross State Product (GSP)/L) in the overall economy	Health care labour share multiplied by growth of nominal health care costs per capita	Baumol variable; growth of nominal GSP per capita; growth of population age 65 and above; growth of unemployment rate; growth of the union membership rate; growth of the poverty rate; growth of housing prices in the previous year	Two-ways FE; 2SLS	They found a positive and significant Baumol effect ranging from 0.009 to 0.037 for U.S states. Thus, they conclude that health care cost in the U.S suffers from Baumol cost-disease effect but in a lesser extent compared to Hartwig (2008) and Colombier (2012).

Appendix: Chapter 4

Appendix 4.1

Mathematical Appendix

This sub-section of the study presents the matrix notations and dimensions of the model set-up described in section 4.2. Notes are provided for some equations to give more details. The set-up begins with:

$$y_{it} = \alpha_i' d_t + \beta_{k,i}' x_{k,it} + u_{it} \tag{1}$$

$$[y_{it}]_{1\times 1} = \begin{bmatrix} \alpha_{i,1} \\ \alpha_{i,2} \\ \vdots \\ \vdots \\ \alpha_{i,n} \end{bmatrix}_{(n\times 1)}^{'} \begin{bmatrix} d_{t,1} \\ d_{t,2} \\ \vdots \\ \vdots \\ d_{t,n} \end{bmatrix}_{(n\times 1)} + \begin{bmatrix} \beta_{i,1} \\ \beta_{i,2} \\ \vdots \\ \vdots \\ \beta_{i,k} \end{bmatrix}_{(k\times 1)}^{'} \begin{bmatrix} x_{it,1} \\ x_{it,2} \\ \vdots \\ \vdots \\ x_{it,k} \end{bmatrix}_{(k\times 1)} + [u_{it}]_{1\times 1} \tag{2}$$

Note 1:

For $i = 1,...,N$, $t = 1,...,T$, and $k = 1$

$$y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1N} \\ y_{21} & y_{22} & \cdots & y_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ y_{T1} & y_{T2} & \cdots & y_{TN} \end{bmatrix}_{(T\times N)} ; d_{t,1} = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ \vdots \\ d_T \end{bmatrix}_{(T\times 1)} ; x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1N} \\ x_{21} & x_{22} & \cdots & x_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ x_{T1} & x_{T2} & \cdots & x_{TN} \end{bmatrix}_{(T\times N)} ;$$

$$\beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \vdots \\ \beta_N \end{bmatrix}_{(N\times 1)}$$

For $i = 1$ and $t = 1$

$$u_{it} = \lambda_{i,m}' f_{t,m} + \varepsilon_{it} \tag{3}$$

$$[u_{it}]_{(1\times 1)} = \begin{bmatrix} \lambda_{i,1} \\ \lambda_{i,2} \\ \vdots \\ \vdots \\ \lambda_{i,m} \end{bmatrix}_{(m\times 1)}^{'} \begin{bmatrix} f_{t,1} \\ f_{t,2} \\ \vdots \\ \vdots \\ f_{t,m} \end{bmatrix}_{(m\times 1)} + [\varepsilon_{it}]_{(1\times 1)} \tag{4}$$

Note 2:

For $i=1$, $t=1,\ldots,T$, and $m=1,\ldots,M$

$$f=\begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1M} \\ f_{21} & f_{22} & \cdots & f_{2M} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ f_{T1} & f_{T2} & \cdots & f_{TM} \end{bmatrix}_{(T\times M)} ; \quad \lambda=\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_M \end{bmatrix}_{(M\times 1)}$$

For $i=1$ and $m=1$

$$f_{i,m}=\begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ \vdots \\ f_T \end{bmatrix}_{(T\times 1)}$$

For $i=1,\ldots,N$, $t=1,\ldots,T$, and $m=1$

$$f_m=\begin{bmatrix} f_1 & f_1 & \cdots & f_1 \\ f_2 & f_2 & \cdots & f_2 \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ f_T & f_T & \cdots & f_T \end{bmatrix}_{(T\times N)} ; \quad \lambda_m=\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_N \end{bmatrix}_{(N\times 1)} ; \quad u=\begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1N} \\ u_{21} & u_{22} & \cdots & u_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ u_{T1} & u_{T2} & \cdots & u_{TN} \end{bmatrix}_{(T\times N)}$$

$$\varepsilon=\begin{bmatrix} \varepsilon_{11} & \varepsilon_{12} & \cdots & \varepsilon_{1N} \\ \varepsilon_{21} & \varepsilon_{22} & \cdots & \varepsilon_{2N} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \varepsilon_{T1} & \varepsilon_{T2} & \cdots & \varepsilon_{TN} \end{bmatrix}_{(T\times N)}$$

$$x_{k,it}=\pi'_{k,i}d_t+\delta'_{k,m,i}g_{m,t}+p_{k,m,i}f_{m,t}+v_{k,it} \qquad (5)$$

For $i=1$, $t=1$, $k=1,\ldots,K$, and $m=1,\ldots,M$

$$\begin{bmatrix} x_{it,1} \\ x_{it,2} \\ \vdots \\ \vdots \\ x_{it,K} \end{bmatrix}_{(K\times 1)} = \begin{bmatrix} \pi_{i,1} \\ \pi_{i,2} \\ \vdots \\ \vdots \\ \pi_{i,K} \end{bmatrix}_{(K\times 1)} [d_t]_{(1\times 1)} + \begin{bmatrix} \delta_{i,11} & \delta_{i,12} & \cdots & \delta_{i,1K} \\ \delta_{i,21} & \delta_{i,22} & \cdots & \delta_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \delta_{i,M1} & \delta_{i,M2} & \cdots & \delta_{i,MK} \end{bmatrix}'_{(M\times K)'} \begin{bmatrix} g_{t,1} \\ g_{t,2} \\ \vdots \\ \vdots \\ g_{t,M} \end{bmatrix}_{(M\times 1)}$$

$$+ \begin{bmatrix} p_{i,11} & p_{i,12} & \cdots & p_{i,1K} \\ p_{i,21} & p_{i,22} & \cdots & p_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ p_{i,M1} & p_{i,M2} & \cdots & p_{i,MK} \end{bmatrix}'_{(M\times K)'} \begin{bmatrix} f_{t,1} \\ f_{t,2} \\ \vdots \\ \vdots \\ f_{t,M} \end{bmatrix}_{(M\times 1)} + \begin{bmatrix} v_{it,1} \\ v_{it,2} \\ \vdots \\ \vdots \\ v_{it,K} \end{bmatrix}_{(K\times 1)} \qquad (6)$$

The observable common factor, d_t (i.e. deterministic trend or seasonal dummies) and the unobservable common factors ($f_{t,m}$) are the same across group but vary over time.

<u>Random Slope Coefficients:</u>

For $k = 1,..., K$ and $i = 1$

$$\beta_{i,k} = \beta_k + \eta_{i,k} \qquad (7)$$

$$\begin{bmatrix} \beta_{i,1} \\ \beta_{i,2} \\ \vdots \\ \vdots \\ \beta_{i,K} \end{bmatrix}_{(K\times 1)} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \vdots \\ \beta_K \end{bmatrix}_{(K\times 1)} + \begin{bmatrix} \eta_{i,1} \\ \eta_{i,2} \\ \vdots \\ \vdots \\ \eta_{i,K} \end{bmatrix}_{(K\times 1)} \qquad (8)$$

$\eta_i \sim IID(\mathrm{O}, \Omega_{\eta_i})$

$\Omega_{\eta_i} \rightarrow (K \times K)$

Note 3:

For $k = 1$ and $i = 1,..., N$

$$\begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \vdots \\ \beta_N \end{bmatrix}_{(N\times 1)} = [\beta]_{(1\times 1)} + \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \vdots \\ \eta_N \end{bmatrix}_{(N\times 1)}$$

$\Omega_{\eta} \rightarrow (N \times N)$

Factor loadings (Y-Equation):

For $m = 1,..., M$ and $i = 1$

$$\lambda_{i,m} = \lambda_m + \zeta_{i,m} \tag{9}$$

$$\begin{bmatrix} \lambda_{i,1} \\ \lambda_{i,2} \\ \vdots \\ \vdots \\ \lambda_{i,M} \end{bmatrix}_{(M \times 1)} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_M \end{bmatrix}_{(M \times 1)} + \begin{bmatrix} \zeta_{i,1} \\ \zeta_{i,2} \\ \vdots \\ \vdots \\ \zeta_{i,M} \end{bmatrix}_{(M \times 1)} \tag{10}$$

$\zeta_i \sim IID(\mathrm{O}, \Omega_{\zeta_i})$

$\Omega_{\zeta_i} \rightarrow (M \times M)$

Note 4:

For $m = 1$ and $i = 1,..., N$

$$\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_N \end{bmatrix}_{(N \times 1)} = [\lambda]_{(1 \times 1)} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \vdots \\ \vdots \\ \zeta_N \end{bmatrix}_{(N \times 1)}$$

$\Omega_{\zeta} \rightarrow (N \times N)$

Factor loadings (X-Equation):

For $i = 1$

$$\delta_{k,m,i} = \delta_{k,m} + \zeta_{k,m,i} \tag{11}$$

$$\begin{bmatrix} \delta_{i,11} & \delta_{i,12} & \cdots & \delta_{i,1K} \\ \delta_{i,21} & \delta_{i,22} & \cdots & \delta_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \delta_{i,M1} & \delta_{i,M2} & \cdots & \delta_{i,MK} \end{bmatrix}_{(M \times K)} = \begin{bmatrix} \delta_{11} & \delta_{12} & \cdots & \delta_{1K} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \delta_{M1} & \delta_{M2} & \cdots & \delta_{MK} \end{bmatrix}_{(M \times K)} + \begin{bmatrix} \zeta_{i,11} & \zeta_{i,12} & \cdots & \zeta_{i,1K} \\ \zeta_{i,21} & \zeta_{i,22} & \cdots & \zeta_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \zeta_{i,M1} & \zeta_{i,M2} & \cdots & \zeta_{i,MK} \end{bmatrix}_{(M \times K)} \tag{12}$$

$$p_{k,m,i} = p_{k,m} + \zeta_{k,m,i} \tag{13}$$

$$\begin{bmatrix} p_{i,11} & p_{i,12} & \cdots & p_{i,1K} \\ p_{i,21} & p_{i,22} & \cdots & p_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ p_{i,M1} & p_{i,M2} & \cdots & p_{i,MK} \end{bmatrix}_{(M\times K)} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1K} \\ p_{21} & p_{22} & \cdots & p_{2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ p_{M1} & p_{M2} & \cdots & p_{MK} \end{bmatrix}_{(M\times K)} + \begin{bmatrix} \zeta_{i,11} & \zeta_{i,12} & \cdots & \zeta_{i,1K} \\ \zeta_{i,21} & \zeta_{i,22} & \cdots & \zeta_{i,2K} \\ \vdots & \vdots & \cdots & \vdots \\ \vdots & \vdots & \cdots & \vdots \\ \zeta_{i,M1} & \zeta_{i,M2} & \cdots & \zeta_{i,MK} \end{bmatrix}_{(M\times K)} \tag{14}$$

$$\zeta_i \sim IID\left(\mathrm{O},\Omega_{\zeta_i}\right)$$

$$\Omega_{\zeta_i} \rightarrow (M\times K)\times(M\times K)$$

Note 5:

For $i=1$ and $k=1$

$$p_{k,m,i} = p_{k,m} + \zeta_{k,m,i}$$

$$\begin{bmatrix} p_{k,i,1} \\ p_{k,i,2} \\ \vdots \\ \vdots \\ p_{k,i,M} \end{bmatrix}_{(M\times 1)} = \begin{bmatrix} p_{k,1} \\ p_{k,2} \\ \vdots \\ \vdots \\ p_{k,M} \end{bmatrix}_{(M\times 1)} + \begin{bmatrix} \zeta_{k,i,1} \\ \zeta_{k,i,2} \\ \vdots \\ \vdots \\ \zeta_{k,i,M} \end{bmatrix}_{(M\times 1)}$$

$$\zeta_{k,i} \sim IID\left(\mathrm{O},\Omega_{\zeta_{k,i}}\right)$$

$$\Omega_{\zeta_{k,i}} \rightarrow (M\times M)$$

For $k=1$ and $m=1$

$$p_{k,m,i} = p_{k,m} + \zeta_{k,m,i}$$

$$\begin{bmatrix} p_{k,m,1} \\ p_{k,m,2} \\ \vdots \\ \vdots \\ p_{k,m,N} \end{bmatrix}_{(N\times 1)} = \left[p_{k,m}\right]_{(1\times 1)} + \begin{bmatrix} \zeta_{k,m,1} \\ \zeta_{k,m,2} \\ \vdots \\ \vdots \\ \zeta_{k,m,N} \end{bmatrix}_{(N\times 1)}$$

$$\zeta_{k,m} \sim IID\left(\mathrm{O}, \Omega_{\zeta_{k,m}}\right)$$

$$\Omega_{\zeta_{k,m}} \rightarrow (N \times N)$$

Appendix 4.2

Pesaran's (2006: 972-973) CCE Estimator Assumption II

This appendix is a supplementary note on the second assumption underlying the Pesaran's (2006:972-973) CCE estimator. The assumption states that "individual specific errors in Y (ε_{it}) and X ($\amalg_{it}$) are distributed independently for all i, j, t and t'".

For each i, ε_{it} and $\amalg_{it}$ are $(T \times 1)$ and $(T \times K)$ matrices respectively.

For each cross-section unit, i, ε_{it} and $\amalg_{it}$ follow linear stationary processes with ABSOLUTE SUMMABLE AUTOCOVARIANCES-(i.e. the covariance structure is stable over time):

$$\varepsilon_{it} = \sum_{\ell=0}^{\infty} a_{i\ell}\xi_{i,t-\ell} \tag{15}$$

$$\amalg_{it} = \sum_{\ell=0}^{\infty} S_{i\ell}V_{i,t-\ell} \tag{16}$$

$t = 1,.,.,.,T$
$t \in \ell$
Where $\ell = 0, \pm 1, \pm 2, \ldots \infty$

ξ_t is random variables called *innovation* process as it represents a part of y_t that is unexplained and unpredictable given the past values of $y_{t-1,} y_{t-2,} \ldots$.
ξ_{it} and V_{it} are IID $(0, \mathrm{I}_{k+1})$

<u>RESIDUALS IN Y</u>

<u>(1) SUMMABLE AUTOCOVARIANCES</u>

For each cross-section unit, i:

$$\sum a_i = \sum \ \mathrm{Cov}(\varepsilon_t, \varepsilon_s) = \sum \begin{bmatrix} 1 & a_{1,2} & \cdots & a_{1,T} \\ a_{2,1} & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & \vdots \\ a_{T,1} & \cdots & a_{T,T-1} & 1 \end{bmatrix}_{T \ X \ T} \tag{17}$$

The absolute row-column difference ($j = |t-(t-1)|$) of each of the elements in the matrix represents the AUTOCOVARIANCE at lag j. It also indicates the existence of autocorrelation.

(2) VARIANCE

Variance for each i **th cross-section unit is**:

$$\frac{\sum_{\ell=0}^{\infty}\left(\varepsilon_{t-\ell}-\bar{\varepsilon}_t\right)^2}{T} = \sum_{\ell=0}^{\infty}\sigma_\ell^2 = Var\left(\varepsilon_{it}\right) = \sum_{\ell=0}^{\infty} a_{ie}^2 = \sigma_i^2 < \infty \tag{18}$$

Recall: $t = 1,.,.,., T$ $t \in \ell$ Where $\ell = 0, \pm 1, \pm 2, . . . \infty$

For a single cross-section unit, the variance at time t across all considered periods is represented as the sum of the T x 1 vector:

$$\sum_{\ell=0}^{\infty}\sigma_\ell^2 = \sum_{\ell=0}^{\infty}\begin{bmatrix} \dfrac{\left(\varepsilon_{t-\ell}-\bar{\varepsilon}_t\right)^2}{T} \\ \vdots \\ \vdots \\ \dfrac{\left(\varepsilon_{t-\ell}-\bar{\varepsilon}_t\right)^2}{T} \end{bmatrix} = \sigma_i^2 < \infty \tag{19}$$

NOTE:

- Pesaran (2006) indicated that the variance varies across each cross-section units (see Eq.(18));
- The sum of variances within each cross-section units is less than ∞. It is a necessary condition for stationarity (see Wold (1938) decomposition theorem);

Also, the variance for each specific cross-section unit is less than or equal to the average of variances for all cross-section units:

$$\sigma_i^2 \le \frac{1}{n}\sum_{i=1}^{n}\sigma_i^2 = \bar{\sigma}^2 < \infty \tag{20}$$

(3) CONSTRUCTING VARIANCE-COVARIANCE MATRIX for each i

Re-representing (19) as symmetric and identity matrix $(T \times T)$ with variance at lag j as the diagonal elements:

Combining (17) and (19) for each cross-section units gives:

$$E(\varepsilon_t \varepsilon_t') = \sigma_i^2 \cdot a_i = \sigma_i^2 \cdot \begin{bmatrix} 1 & a_{1,2} & \cdots & a_{1,T} \\ a_{2,1} & 1 & \vdots & \vdots \\ \vdots & \vdots & 1 & \vdots \\ a_{T,1} & \cdots & a_{T,T-1} & 1 \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_{i1}^2 & \sigma_i^2 a_{1,2} & \cdots & \sigma_i^2 a_{1,T} \\ \sigma_i^2 a_{2,1} & \sigma_{i2}^2 & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_i^2 a_{T,1} & \cdots & \sigma_i^2 a_{T,T-1} & \sigma_{iT}^2 \end{bmatrix}_{T \ X \ T} \quad (21)$$

NOTE: It is assumed that the variance of ε_t is the same for all T i.e. Homoskedasticity.

RESIDUALS IN X

(1) SUMMABLE AUTOCOVARIANCES

The errors in X regressors can be represented as $(K \times 1)$ matrix with each element as block of T matrix for each cross-section:

$$\amalg_{it} = \begin{bmatrix} v_{i,1} \\ v_{i,2} \\ \vdots \\ v_{i,k} \end{bmatrix}_{K \ X \ 1} \quad (22)$$

Alternatively, for each cross-section unit with K explanatory variables over time, the residual is a $(T \times K)$ matrix:

$$\amalg_{it} = \begin{bmatrix} v_{i,t1,1} & v_{i,t1,2} & \cdots & v_{i,t1,k} \\ v_{i,t2,1} & \vdots & \vdots & \vdots \\ \vdots & \vdots & \vdots & \vdots \\ v_{i,T,1} & \cdots & \cdots & v_{i,T,k} \end{bmatrix}_{T \ X \ K} \quad (23)$$

Using the following formulae compute the variance-covariance matrix for specific cross-section unit:

$$E(\amalg_t \amalg_t') = \amalg_t - \mathrm{N} \cdot \amalg_t \left(1/T \right) \tag{24}$$

Where N is a $(T \times T)$ matrix with one as elements. The diagonal elements are the variance for each explanatory variable and off-diagonal elements are the covariance and each represents a matrix of $(T \times T)$ matrix with ones along the diagonal as shown in (17).

$$E(\amalg_t \amalg_t') = \begin{bmatrix} \Sigma_{11} & S_{1,2} & \cdots & S_{1,k} \\ S_{2,1} & \ddots & \vdots & S_{2,k} \\ \vdots & \vdots & \ddots & \vdots \\ S_{k,1} & \cdots & \cdots & \Sigma_{kk} \end{bmatrix}_{K\ X\ K} \tag{25}$$

For each group specific, the auto-covariance is the sum of the off-diagonal elements $(T \times (T-1))$:

$$S_i = \sum_{r=1}^{k} \sum_{c=1}^{k} S_{i,r,c} \tag{26}$$

(2) VARIANCE

Variance for each i **th cross-section units is**:

The sum of the elements on the diagonal matrix given as:

$$\Sigma_i = \sum_{r=1}^{k} \Sigma_{i,r,r} \tag{27}$$

The average of variances for all cross-section units is less than ∞ i.e.:

$$\Sigma_i \leq \frac{1}{n} \sum_{i=1}^{n} \Sigma_i = \overline{\Sigma} < \infty \tag{28}$$

NOTE: for all i, $\sigma_i^2 > 0$ **and** Σ_i $(K \times K)$ is a positive definite matrix.

Appendix 4.3

Derivation of Unobservable Common Factors Proxies when $k=1$ and $m=1$:

For $k=1$ and $m=1$

$$y_{it}=\alpha_i' d_t+\beta_{k,i}' x_{k,it}+u_{it} \tag{29}$$

$$u_{it}=\lambda_{i,m}' f_{t,m}+\varepsilon_{it} \tag{30}$$

Random Slope Coefficients:

$$\beta_{i,k}=\beta_k+\eta_{i,k}$$

(31)

Factor loadings (Y-Equation):

$$\lambda_{i,m}=\lambda_m+\zeta_{i,m} \tag{32}$$

Substitute (30), (31) and (32) into (29), give:

$$y_{it}=\alpha_i' d_t+\beta' x_{it}+\eta_i' x_{it}+\lambda' f_t+\zeta_i' f_t+\varepsilon_{it} \tag{33}$$

Following the assumptions in Pesaran (2006, pp. 972-973) that the error disturbances have a mean of zero for all i, j, and t:

$$\eta_i \sim IID\left(O,\Omega_{\eta_i}\right)$$

$$\zeta_i \sim IID\left(O,\Omega_{\zeta_i}\right)$$

$$\varepsilon_{it} \sim IID\left(O,\Omega_{\varepsilon}\right)$$

Taking the cross-sectional average of Eq.(33) at each time period gives:

$$\bar{y}_t=\bar{\alpha}' d_t+\bar{\beta}'\bar{x}_t+\bar{\lambda}' f_t$$

(34)

$$\bar{\lambda}' f_t=\bar{y}_t-\bar{\alpha}' d_t-\bar{\beta}'\bar{x}_t$$

(35)

OLS estimation of the above gives:

$$\bar{\lambda}' f_t=\hat{\bar{y}}_t-\hat{\bar{\alpha}}' d_t-\hat{\bar{\beta}}'\bar{x}_t \tag{36}$$

Since the common factor loading vector ($\bar{\lambda}$) is fixed across i, then $\bar{\lambda}=\lambda$ and it is non-zero.

$$f_t=(\lambda')^{-1}\left(\hat{\bar{y}}_t-\hat{\bar{\alpha}}' d_t-\hat{\bar{\beta}}'\bar{x}_t\right) \tag{37}$$

According to Pesaran (2006), the unobservable common factor is a function of the observables i.e. $f_t=g\left(\bar{y}_t,\bar{x}_t\right)$ if the deterministic trend is 1 ($d_t=1$).

Appendix: Chapter 5

Table 5.3: Review of Selected Empirical Studies on Income Elasticity of Health Expenditures

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
1	**Chakroun (2010)**	Health care expenditure and GDP: An international panel smooth transition approach	17 OECD countries (1975 – 2003)	Real per capita health expenditure	Real per capita GDP, proportion of population aged 65 years above, proportion of population under 15, share of public financing, and life expectancy as a measure of life expectancy and a threshold parameter	Panel Smooth Threshold Regression	Necessity	
2	**Di Matteo (2003)**	The income elasticity of health care spending: A comparison of parametric and nonparametric approaches	United States state (1980-1997); Canada provinces (1965-2000); 16 OECD countries (1960 - 1997)	Per capita health expenditure	For U.S & OECD: Per capita real gross state product, proportion of population aged 65. For Canada: Real per capita provincial GDP, real per capita provincial revenue from federal cash transfers, proportion of population aged 65 and over	Fixed effect regression (OLS)	Necessity	
3	**Di Matteo & Di Matteo (1998)**	Evidence on the determinants of Canadian provincial government health expenditures: 1965 – 1991	Canada provinces (1965 - 1991)	Per capita health expenditure	Real per capita provincial GDP, real per capita provincial revenue from federal cash transfers, proportion of population aged 65 and over		Necessity (0.77)	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
4	**Hitiris & Posnett (1992)**	The determinants and effects of health expenditure in developed countries	20 OECD countries (1960-1987)	Per capita health spending	GDP per capita, proportion of the population over 65	Fixed effect regression (OLS)	Unity	POSITIVE & SIGNIFICANT: Proportion of the population over 65
5	**Di Matteo (2005)**	The macro determinants of health expenditure in the United States and Canada: assessing the impact of income, age distribution and time	US states (1980 - 1998); Canada provinces (1975 - 2000)	Per capita health expenditure	For U.S: Per real capita, real gross state product, proportion of population aged: 0-24, 25-44, 45-64, 65-84, 65 and over, 85 and over. For Canada: real per capita provincial government total health expenditure, real per capita provisional GDP, real per capita provincial revenue from federal cash transfers, proportion of population aged: 0-17, 18-44, 45-64, 65-74, 75 and over. Time as a measure of technology.	Two-way fixed effect regression (OLS)	Necessity	POSITIVE & SIGNIFICANT: Time, population aged 25-44, 65-84, and 65-over (U.S); population aged 18-44 (Canada), and provisional revenue (Canada)

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
6	**Di Matteo (2000)**	The determinants of the public-private mix in Canadian health care expenditures: 1975-1996	Canada (1975-1996)	Ratio of public-private health expenditure centralization	Real per capita GDP, proportion of population aged 65 and over, individual income share of top and bottom quintile, real per capital federal health transfers, Canada health and social transfer, established program financing	OLS	Necessity (negative)	POSITIVE & SIGNIFICANT: Real per capital federal health transfers. NEGATIVE & SIGNIFICANT: Dummy for established program financing
7	**Gbesemete & Gerdtham (1992)**	Determinants of health care expenditure in Africa: A cross-sectional Study	30 African countries (1984)	Health care expenditure per capita	Percentage of births attended by health staff, Gross national product per capita, proportion of populated aged under 15, proportion of urban population, crude birth rates, and foreign aid received per capita	Cross-section regression (OLS)	Necessity	POSITIVE & SIGNIFICANT: Percentage of births attended by health staff, and foreign aid received per capita
8	**Murthy & Okunade (2009)**	The core determinants of health expenditure in the African context: Some econometric evidence for policy	44 African countries (2001)	Real per capita health expenditure	Real per capita GDP, real per capita foreign aid, proportion of population aged 65 and over, and maternal mortality per 1000 persons	Cross-section regression (OLS) and Least Absolute Error (LAE) estimator	Necessity	POSITIVE & SIGNIFICANT: real per capita foreign aid

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
9	**Sen (2005)**	Is health care a luxury? New Evidence from OECD data	15 OECD countries (1990-1998)	Real per capita health expenditure	Real per capita GDP, Demand variables (infant mortality rates per 100,000 population and proportion of population aged 65 years and above), and supply variables (average length of patient stay in hospital and number of physicians per 1,000 of population)	Two-way fixed effects [(OLS), Weighted Least Squares (WLS), Generalized Least Squares (GLS), and Instrumental Variables (IV)]	Necessity (0.21 – 0.51)	POSITIVE & SIGNIFICANT: Average length of patient stay in hospital and number of physicians per 1,000 of population. NEGATIVE & SIGNIFICANT: proportion of population aged 65 years and above.
10	**Freeman (2003)**	Is health care a necessity or a luxury? Pooled estimates of income elasticity from US state-level data	US states (1966-1998)	Health care expenditure	Disposable personal income	OLS, Dynamic OLS, Fully Modified OLS	Necessity (0.817 – 0.844)	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
11	**Dreger & Reimers (2005)**	Health care expenditures in OECD countries: A panel unit root and cointegration analysis	21 OECD countries (1975-2001)	Real per capita health expenditure	Real per capita GDP, life expectancy, infant mortality rate, and proportion of population aged 65-above	Fully Modified OLS and Dynamic OLS	Necessity	POSITIVE & SIGNIFICANT: Life expectancy and share of elderly population. NEGATIVE & SIGNIFICANT: Infant mortality rate
12	**Baltagi & Moscone (2010)**	Health care expenditure and income in the OECD reconsidered: Evidence from panel data	20 OECD (1971-2004)	Per capita total health expenditure	Public health expenditure as a share of total health expenditure, dependency rates for old and young people [ratio of population aged 65-over to population aged 15-64; ratio of population aged 0-14 to population aged 15-64 respectively]	Fixed effect, Spatial Maximum Likelihood Estimator, and Common Correlated Effect Pooled (CCEP) estimators	Necessity	POSITIVE & SIGNIFICANT: Dependency rate of young people
13	**Hall & Jones (2007)**	The value of life and the rise in health spending	United States (1950-2000 (five years average))	Health expenditure	GDP, proportion of population in different aged groups, and life expectancy (proxy for value of life)	Calibrated Model	Luxury	POSITIVE & SIGNIFICANT: Life expectancy

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
14	**Moscone & Tosetti (2010)**	Health expenditure and income in the United States	49 US States (1980-2004)	Real per capita health expenditure	Real per capita disposable income, proportion of population aged 65-over, number of beds, number of doctor, and proportion of public spending and total health expenditure.	Fixed Effects, Common Correlated Effect (CCE) Pooled and Mean Group	Necessity	POSITIVE & SIGNIFICANT: Proportion of population aged 65-over, number of doctor, and proportion of public spending and total health expenditure.
15	**Roberts (1999)**	Sensitivity of elasticity estimates for OECD health care spending:	20 OECD countries (1960-1993)	Per capita health care expenditure	GDP per capita, percentage of publicly funded health care spending, percentage of the population aged over 65 years, ratio of health price index to the GDP deflator, time as a proxy of technical changes	Cross-section regression, Pooled OLS, and Mean Group estimator (Static and Dynamic model)	Luxury	POSITIVE & SIGNIFICANT: percentage of publicly funded health care spending, and ratio of health price index to the GDP deflator
16	**Parkin, McGuire, & Yule (1987)**	Aggregate health care expenditure and national income	23 OECD countries (1980)	Health expenditure per person (real and nominal terms)	GDP per person (real and nominal terms)	Cross-section regression	Necessity	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
17	**Getzen (2000)**	Health care is an individual necessity and a national luxury: applying multilevel decision models to the analysis of health care expenditures	42 studies (1967-1999)	Health expenditure (private, public and regional)	Gross Domestic Product	Meta Review of previous studies	Necessity (Individual and Regional); Luxury (National expenditure)	
18	**Blomqvist & Carter (1997)**	Is health care really a luxury?	24 OECD (1960-1991)	Real per capita health care expenditure	Real GDP per capita, percentage of population aged 65 years and over, and time (proxy for technological progress)	OLS and Phillips-Loretan estimator	Necessity (0.976, Eq. 13)	POSITIVE & SIGNIFICANT: Time trend (measure of medical technological progress)
19	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Total health expenditure as a percentage of gross domestic product	Gross Domestic Product Per Capita	Cross-section regression	Necessity (Low, Medium-to-high, High, and All income group)	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
20	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Out-of-pocket payments as a percentage of total health expenditure	Gross Domestic Product Per Capita	Cross-section regression	Necessity (Low, Medium-to-high, High, and All income group)	
22	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Public health expenditure as a percentage of total public expenditure	Gross Domestic Product Per Capita	Cross-section regression	Necessity (Low, Medium-to-high, High, and All income group)	
23	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Total health expenditure per capita as a function of income per capita	Gross Domestic Product Per Capita	Cross-section regression	Luxury (Low, Medium-to-high, High, and All income group)	
24	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Out-of-pocket payments per capita as a function of income per capita	Gross Domestic Product Per Capita	Cross-section regression	Luxury(Low income group); Necessity (Medium-to-high, High, and All income)	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
25	**Musgrove, Zeramdini, Carrin (2002)**	Basic patterns in national health expenditure	191 World Health Organisation (WHO) Member States (1997)	Total public expenditure per capita as a function of income per capita	Gross Domestic Product Per Capita	Cross-section regression	Luxury (Low, Medium-to-high, High, and All income group)	
26	**Okunade & Murthy (2002)**	Technology as a “major driver” of health care costs: a cointegration analysis of the Newhouse conjecture	US (1960-1997)	Per capital real health care expenditure	Per capita real disposable personal income and technological changes proxied by total R&D spending and health sector R&D spending	Time series regression (OLS)	Luxury	POSITIVE & SIGNIFICANT: total R&D spending and health sector R&D spending

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
27	**Gerdtham, Sogaard, Andersson & Jonsson (1992)**	An econometric analysis of health care expenditure: a cross-section study of the OECD countries	19 OECD countries (1987)	Health care expenditure per capita	GDP per capita, ratio of PPP for medical care to PPP for GDP, number of practicing physicians per capita multiplied by 1000, share of total health care expenditure used on inpatient health care, share of total health care expenditure used in public expenditure, dummy variables (fee-for-service in outpatient care, global budgeting in hospital care), female participation ratio (labour force as a ratio of population aged 15-64 years), ratio of population 65 years and over to population aged 15-64, and share of population living in towns with over 500,000 inhabitants	Cross-section regression	Luxury	POSITIVE & SIGNIFICANT: share of total health care expenditure used on inpatient health care, fee-for-service in outpatient care, and ratio of population 65 years and over to population aged 15-64. NEGATIVE & SIGNIFICANT: number of practicing physicians per capita multiplied by 1000, and share of total health care expenditure used in public expenditure.

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
28	**Murthy & Okunade (2016)**	Determinants of U.S. health expenditure: Evidence from autoregressive distributed lag (ARDL) approach to cointegration	U.S (1960-2012)	Real per capita health spending	Per capita real income, population percent above 65 years, and the level of health R&D (as a proxy for technology)	ARDL model	Necessity	POSITIVE & SIGNIFICANT: Population percent above 65 years, and the level of health R&D (as a proxy for technology)
29	**Lv & Xu (2016)**	Does intelligence affect health care expenditure? Evidence from a cross-country analysis	172 developed and developing countries (2009-2013)	Real health care expenditure per capita	GDP per capita, Percentage of population age 65, Voice and accountability, Government effectiveness, and national IQ scores	Cross-section regression	Luxury (High IQ countries above 95% threshold); Necessity (Low IQ countries below 95% threshold)	POSITIVE & SIGNIFICANT: GDP per capita, Percentage of population age 65, Voice and accountability, interactive term (GDP per capita and IQ). NEGATIVE & SIGNIFICANT: IQ or cognitive ability
30	**Newhouse (1977)**	Medical care expenditure: a cross-national survey	13 developed countries (1972)	Per capita medical-care expenditure	GDP per capita	Cross-section regression	Luxury	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
31	**Barros (1998)**	The black box of health care expenditure growth determinants	24 OECD countries (1960,19701980, & 1990)	Per capita health expenditure growth	First year per capita health expenditure growth, GDP average growth rate, percentage change in population over 65, and dummy variables (time, types of health system [public reimbursement and public integrated], and gatekeeping)	Fixed effect regression	Necessity	NEGATIVE & SIGNIFICANT: First year per capita health expenditure growth
32	**Xu, Saksena & Holly (2011)**	The determinants of health expenditure: a country-level panel data analysis	143 developing countries with population greater than 300,000 (1995-2008)	Government health expenditure per capita	GDP per capita, total government expenditure as a share of GDP, proportion of population aged 60 years above, incidence of tuberculosis per 100,000 people, out-of-pocket expenditure as a share of total health expenditure, external aids and time	Fixed effect regression (OLS) and GMM	Luxury (Low-income); and Necessity (lower-middle, upper-middle, and high income)	POSITIVE & SIGNIFICANT: total government expenditure as a share of GDP; and time. NEGATIVE & SIGNIFICANT: External aids

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
33	**Xu, Saksena & Holly (2011)**	The determinants of health expenditure: a country-level panel data analysis	143 developing countries with population greater than 300,000 (1995-2008)	Out-of-pocket health expenditure per capita	GDP per capita, total government expenditure as a share of GDP, proportion of population aged 60 years above, incidence of tuberculosis per 100,000 people, out-of-pocket expenditure as a share of total health expenditure, external aids and time	Fixed effect regression (OLS) and GMM	Luxury (Low-income); and Necessity (lower-middle, upper-middle, and high income)	NEGATIVE & SIGNIFICANT: Time
34	**Xu, Saksena & Holly (2011)**	The determinants of health expenditure: a country-level panel data analysis	143 developing countries with population greater than 300,000 (1995-2008)	Total health expenditure per capita	GDP per capita, total government expenditure as a share of GDP, proportion of population aged 60 years above, incidence of tuberculosis per 100,000 people, out-of-pocket expenditure as a share of total health expenditure, external aids and time	Fixed effect regression (OLS) and GMM	Necessity (Low-income, lower-middle, upper-middle, and high income)	POSITIVE & SIGNIFICANT: total government expenditure as a share of GDP, proportion of population aged 60 years above , and time
35	**Lago-Penas, Cantarero-Prieto, & Blazquez-Fernandez (2013)**	On the relationship between GDP and health care expenditure: A new look	31 OECD countries (1970-2009)	Per capital total health expenditure	Per capita GDP, GDP trend (computed using Hodrick-Prescott filter), negative and positive GDP gaps between GDP and GDP trend, and percentage of population over 64 years old	Panel Corrected Standard Errors (PSCE) estimator [robust to both cross-sectional heteroscedasticity and error correlation]	Necessity	POSITIVE & SIGNIFICANT: GDP trend, positive and negative GDP gap, and old age population

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
36	**Fan & Savedoff (2014)**	The health financing transition: A conceptual framework and empirical evidence	126 WHO member countries (developed and developing)	Total health expenditure per capita	GDP per capita, proportion of population over age 60, proportion of government expenditure of GDP, and Time	Fixed effect regression (OLS)	Necessity	POSITIVE & SIGNIFICANT: proportion of government expenditure of GDP, and Time
37	**Fan & Savedoff (2014)**	The health financing transition: A conceptual framework and empirical evidence	126 WHO member countries (developed and developing)	Government health expenditure per capita	GDP per capita, proportion of population over age 60, proportion of government expenditure of GDP, and Time	Fixed effect regression (OLS)	Luxury	POSITIVE & SIGNIFICANT: Proportion of government expenditure of GDP, and old age.
38	**Fan & Savedoff (2014)**	The health financing transition: A conceptual framework and empirical evidence	126 WHO member countries (developed and developing)	Out-of-pocket health expenditure per capita	GDP per capita, proportion of population over age 60, proportion of government expenditure of GDP, and Time	Fixed effect regression (OLS)	Luxury	POSITIVE & SIGNIFICANT: Proportion of population over age 60
39	**Fan & Savedoff (2014)**	The health financing transition: A conceptual framework and empirical evidence	126 WHO member countries (developed and developing)	Out-of-pocket health expenditure as a share of total health expenditure	GDP per capita, proportion of population over age 60, proportion of government expenditure of GDP, and Time	Fixed effect regression (OLS)	Income has no significant effect	POSITIVE & SIGNIFICANT: Proportion of population over age 60. NEGATIVE & SIGNIFICANT: Other variables

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
40	**Caporale, Cunad, Gil-Alana, & Gupta (2015)**	The relationship between healthcare expenditure and disposable personal income in the US States: A fractional integration and cointegration	50 US states (1966-2009)	Real healthcare expenditure per capita	Real GDP per capita	OLS regression (for individual country)	Necessity	
41	**Freeman (2012)**	Is health care a necessity or a luxury? New evidence from a panel of U.S. state-level data	50 US states (1966-2009)	Real healthcare expenditure per capita	Real GDP per capita	OLS regression (for individual country) and Pooled OLS	Necessity	
42	**Mello-Sampayo & Sousa-Vale (2014)**	Financing health care expenditure in the OECD countries: Evidence from a heterogeneous, cross-section dependent panel	30 OECD countries (1990-2009)	Real total health expenditure per capita	Real GDP per capita, population aged over 65 years, population aged under 15 years, infant mortality rate, public health expenditure as a share of total health expenditure, private health expenditure as a share of total health expenditure	Fixed effect regression (OLS), and Common Correlated Effected Pooled (CCEP) Estimator	Income has no significant effect	POSITIVE & SIGNIFICANT: public and private health expenditure as a share of total health expenditure

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
43	**Khan, Khan, Razil, Sahfie, Shehzada, Krebs, & Sarvghad (2016)**	Health care expenditure and economic growth in SAARC countries (1995-2012): A panel causality analysis	8 SAARC countries (1995-2012)	Per capita health care expenditure	Per capita GDP, labour force, literacy rate, and elderly population of age 65 and above, life expectancy at birth	Panel Dynamic OLS, and SUR	Necessity	POSITIVE & SIGNIFICANT: Labour force, literacy rate, and elderly population of age 65 and above
44	**Okunade, Karakus, Okeke (2004)**	Determinants of health expenditure growth of the OECD countries: Jacknife resampling plan estimates	25 OECD countries (1968-1997)	Real Per capita health care spending growth	Real per capita GDP growth, growth in the relative price of health care, growth in doctor density per 1000 population, rates of growth in the population segments over 65 years and under 15 years, growth of government spending for health as a share of total health expenditure	Jackniffing resampling estimator	Necessity	

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
45	**Okunade (2005)**	Analysis and implication of the determinants of healthcare expenditure in African countries	26 African countries (1995)	Real per capita total health expenditure	Real per capita GDP, gini coefficient of income distribution, dependency ratio of population, percentage of population below aged 15 years, population per nurse, population per medical doctor, mortality rate, percentage of urbanized population, per capita official development assistance, percentage of births attended by trained health care personnel, corruption index, and intra-country conflict (civil war) during the 1990s	Cross-sectional regression (OLS)	Necessity	POSITIVE & SIGNIFICANT: Intra-country war, percentage of population below aged 15 years, and percentage of births attended by trained health care personnel. NEGATIVE & SIGNIFICANT: Gini coefficient of income distribution
46	**Murthy (2004)**	Health care expenditures in Africa: An econometric analysis	44 African countries (2001)	Real per capita total health expenditure	Real per capita GDP, and per capita foreign aid	Cross-sectional regression (OLS)	Unity (Normal goods)	POSITIVE & SIGNIFICANT: per capita foreign aid

S/N	Author(s)/ (Year)	Title	Scope	Dependent variable	Independent Variable(s)	Method/Model	Nature of Health Good	Other Findings
47	**Jaunky and Khadaroo (2008)**	Health care expenditure and GDP: An African perspective	28 African countries (1991-2000)	Real per capita total health expenditure, real per capita public and private health expenditures	Real per capita GDP	Pooled OLS, Fixed Effect OLS, Between Effects OLS, GMM (Arellano-Bond), Prais-Winsten, and ECM	Luxury for public expenditure and necessity for private expenditure	
48	**Lv and Zhu (2014)**	Health care expenditure and GDP in African countries: Evidence from Semiparametric estimation with panel data	42 African countries (1995-2009)	per capita total health expenditure	GDP per capita, population age 65 and above, and infant mortality rate per 1,000 live birth	FE OLS	Necessity	POSITIVE & SIGNIFICANT: population age 65 and above. NEGATIVE & SIGNIFICANT: infant mortality rate

Source: Author's compilation

Table A5.2: Test of Slope Homogeneity

Dependent variables	lnTHE	lnGHE	lnOPE
Chi-square	35688.19***	14757.10***	69959.30***
p-value	0.000	0.000	0.000

Estimated Model

$$HCE_{it} = \alpha + \beta_{i,1}GDP_{it} + \beta_{i,2}LEX_{it} + \beta_{i,3}INM_{it} + \beta_4 P65_{it} + \beta_{i,5}P15_{it} + \beta_{i,6}ODA_{it} + \beta_{i,7}GFC_{it} + \mu_i + \omega_{it}$$

Hypothesis

$$H_0 : \beta_{1,1} = ... = \beta_{1,47}$$

Note: The models are estimated using the Random Coefficient Model (RCM). The reported statistic was suggested by Swamy (1970). It examines the difference between group-specific OLS estimate of the slope β_1 while ignoring the panel data structure and the matrix-weighted average of the group-specific OLS estimators (see Johnston & DiNardo, 1997 for details).

*, **, and *** denote statistical significance at 10%, 5% and 1% level respectively